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DEMAND FORECASTING WITH PROGRAM FACTORS

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AMC Inventory Research Office
Philadelphia, Pennsylvania

September 1975

FINAL REPORT
IRO REPORT NO. 182

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number):

Empirical demand forecasting studies have raised doubt about the often-made assumption that repair part demand is proportional to end-item usage. The study was made to test this assumption using a data base consisting of demands on the Army Aviation Systems Command National Inventory Control Point (AVSCOM NICP) for thousands of stocked items. A simulation of the NICP supply function was used to test the assumption and various proposed forecasting algorithms. The criterion was least holding and ordering cost for constant

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ABSTRACT (CONT)

time-weighted requisitions short. The assumption that demand is proportional to end-item program was supported at least for the items responsible for the largest part of the costs, and an improved algorithm was found.

Information and data contained in this document are based on input available at the time of preparation. Because the results may be subject to change, this document should not be construed to represent the official position of the U.S. Army Materiel Command unless so stated.

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SUMMARY

1. Background

For many years, the Army has used program factors such as flying hours, miles travelled, end item populations and rounds fired in the forecasting of demand for repair parts. In using program factors, the assumption is traditionally made that demand is directly proportional to the level of activity - that is, an increase of 20% in flying hours, for example, will cause a 20% increase in parts demand. However, a number of studies have raised doubt about this assumption, as evidenced in reports cited in the Selected Bibliography contained in this report. Since there is some conflict in the evidence of these studies, this work was undertaken in an attempt to resolve the issue.

2. Scope

This study is limited to developing procedures for the forecasting of worldwide recurring demands for Army managed class IX secondary items (repair parts and spares) including stock fund and PEMA items. Recurring demand is that portion of total demand which is due ultimately to failures of parts in service. Specifically excluded from recurring demand are initial issues of parts when new units are activated or new weapon systems are fielded (provisioning), issues for mobilization reserves, and issues to maintenance facilities for rebuild programs. Also excluded are those secondary items that would be expected to receive intensive management making use of specialized information such as life-cycle or closed loop asset data. The procedures are to be applied in the Commodity Command Standard System (CCSS) inventory management function implemented at the Army's National Inventory Control Points. The study was not intentionally limited to aircraft items but the only adequate data available was for such items. However, it is believed that the conclusions may be extended to other than aircraft items.

3. Methodology

First, a number of demand models were considered and appropriate forecasting algorithms were selected. These algorithms and some related techniques were then screened according to how they reacted to trends in aggregate demands.

This screening was done to weed out the worst algorithms in order to save resources in the final selection phase. The ones yielding the smallest mean absolute forecast errors were then compared using a simulation of the individual items in the supply system. The final selection was made on the basis of smallest aggregate simulated inventory cost for constant time-weighted requisitions backordered.

4. Conclusions

The Army's presently used program factor is better than a simple moving average of demand alone. A forecast method based on a regression equation of demand as a function of flying hours is better than the present forecasting method.

There is almost no improvement to be gained in applying different forecast methods to different segments of the item catalog on the basis of unit price, demand rate, dollar value of demand, or dynamic versus nondynamic items.

Finally, there is no improvement in program factor type forecasts due to lagging the demand behind the program data.

5. Recommendations

It is recommended that the regression algorithm be used instead of the currently used factor.

Final implementation should be delayed, however, pending completion of another AMCIRO study on Methodology of Demand Forecasting, which is looking at methods other than the simple moving average which, when combined with the program factor recommended here, might give better forecasts.

CHAPTER 2

PREVIOUS WORK

Previous studies of the relationship between demand and program data by the Navy and Air Force have met with little success. While good correlation has been found for gross measures of demand over many parts [Brown 1956, DSA 1968] the relationship between program data and demand for particular parts has been elusive [Berger 1973, Denicoff 1962, Gabriel 1972, Haber 1967, Markland 1970]. The few positive findings do not relate well to our problem. A study by RAND [Astrachan 1961] compared the forecasting accuracy of a simple program factor to that of three program factors with built-in safety levels, and to three specialized methods that require more detailed knowledge of part history than is available for ordinary repair parts. (These "service life" methods are applicable to expensive components like aircraft engines.) Results were mixed, but the simple program factor did about as well as any of the other methods.

The authors of a thesis presented to the Air Force Institute of Technology [Goldfarb 1967] stated that program data had "...little value as a demand prediction tool..."; however, their results were not completely discouraging. For many of the parts studied demand correlated well with the actual flying hours of the aircraft end items, and the flying hours themselves could be accurately forecasted from the planned hours; however, the authors were cautious about drawing conclusions.

Previous studies have used forecast error as the criterion. Thus the best forecast method was considered to be the one that most reduced the measure of deviation between forecasted and actual demand for the period. However, this raises the question of which measure of deviation to use. Some work has used mean absolute deviation (MAD) and other has used mean squared error. Results, in general, may be different. Another consideration is that some items have a larger impact on supply performance than others - and that some items cost much more than others. For example, a study with Navy data [Denicoff 1962] concluded "...only 59 parts, or three percent of the parts examined, were correlated with flying hours," The author did not know whether this

group of parts represented 3 percent or 30 percent of the total parts budget. It was for this reason that a cost versus performance simulation approach was prescribed by the Office of the Secretary of Defense for Installations and Logistics as the method to be used in validating new forecasting techniques. It has already been used by Inventory Research Office to develop the details of the inventory policy. See "Evaluation of Several VSL/EOQ Models" by Robert L. Deemer and W. Karl Kruse, May 1974, AD 781948, "Frequency of Requirements Determination" by Robert L. Deemer, October 1974, AD A003227, and "Estimation of Demand Variability Parameters" by Alan J. Kaplan, May 1974, AD 781942.

CHAPTER 2

DATA

2.1 Source and Organization

The conclusions in this report are based on studies made using chronological demand data from AVSCOM. Flying hours covering the same period as the demand data were obtained from DCSLOG. All data has been summarized by quarter. For each quarter we have the worldwide totals of the number of requisitions, the quantity demanded and the flying hours. The flying hour totals are broken out by aircraft type/model/series (TMS). The data spans the 28 quarters from January 1967 thru December 1973.

2.2 Weapon Systems

Appendix A, Section V of AR 710-1 associates end items into classes called <u>weapon systems</u>. A two letter code is assigned to each system. The first letter is an A for fixed-wing airplanes, and B for helicopters. The table below contains the TMS codes grouped into weapon systems.

WEAPON-SYSTEM GROUPINGS

WEAPON SYSTEM	AIRCRAFT TYPE / MODEL / SERIES								
AA	RU1A	U1A							
AB	RU6A	U6A							
AD	RU8D	U8D	U8F	[illegible]					
AE	RU9D	U9D	U9C						
AF	U10A								
AG	RU21A	RU21B	RU21C	RU21D	[illegible]	U21A	U21F	U21G	
AH	OV1A	OV1B	OV1C	OV1D					
AK	O1A	O1D	O1E	O1F	[illegible]	P2E	T01D	T41B	T42A
AL	O3								
BA	TH1G	UH1A	UH1B	UH1C	UH1D	UH1H	UH1M		
BC	AH1G	AH1Q							
BD	OH13F	OH13G	OH13H	OH13S	[illegible]				
BE	UH19C	UH19D							
BF	CH21B	CH21C							
BG	OH23B	OH23C	OH23D	OH23F	OH23G				
BH	CH34C	VH34C							
BJ	CH37B								
BK	CH47A	CH47B	CH47C						
BM	CH54A	CH54B							
BN	OH6A	TH55A							
BP	OH58A								

A chart on the next page gives an idea of the appearance of the various aircraft. The heading "DESIGNATION" corresponds to TMS.

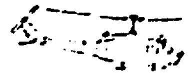
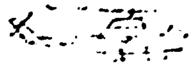
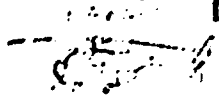
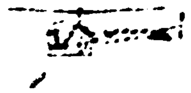
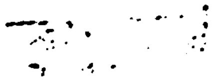
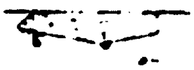
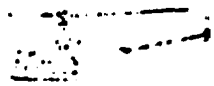
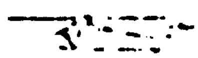
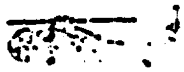
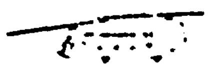
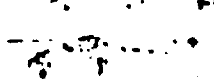
The graph on the following page and those in Appendix 2 show the flying hours and demand quantity by quarter for the first five years for those weapon systems with a reasonably large group of repair parts. The demand and hours have been scaled (as described in the chapter on Model Validation and Selection) so that each sums up to one (unit demanded or hour flown) for the 20-quarter period for each part. The graphs show the average of the scaled values by quarter for a large sample of the parts in each system (the preliminary data base described below).

It can be seen from the graphs that the demand follows the flying hour pattern fairly well on some of the systems. The exceptions are mostly in the form of peaks in demand.

These observations suggest that demand is well correlated to flying hours, and that a program factor would be expected to yield good demand forecasts by the traditional forecast error criterion, at least for this data.

DESIGNATION OF ARMY AIRCRAFT

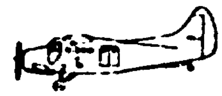
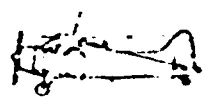
HELICOPTER SERIES

DESIGNATION	ENGINE	POPULAR NAME
UH-1A	T53-L-1A	IROQUOIS BA 
UH-1B	T53-L-5,9,11	
UH-1D	T53-L-5,9,11	
UH-1H	T53-L-13	
AH-1G	T53-53-L-13	COBRA BC 
OH-6A	T63-A5A	CAYUSE BN 
OH-13E	0-335-5D	SIOUX BD 
OH-13G	0-335-5D	
OH-13H	0-435-23C	
OH-13K	6VS-335A	
OH-13S	0-435-25A	
UH-19C	R-1340-57	CHICKASAW BE 
UH-19D	R-1300-3D	
CH-21B	R-1820-103A	SHAWNEE BF 
CH-21C	R-1820-103A	
OH-23B	0-335-5D	RAVEN BG 
OH-23C	0-335-5D	
OH-23D	0-435-23C	
OH-23F	0-540-9	
OH-23G	0-540-9	
CH-34A	R-1820-84A	CHOCTAW BH 
CH-34C	R-1820-84C	
CH-37B	R-2800-54	MOJAVE BJ 
CH-47A	T55-L-5/-7	CHINOOK BK 
CH-47B	T55-L-7C	
CH-47C	T55-L-11	
CH-54A	T73-P-1	TARHE BM 
AH-56A	T64-GE-16	CHEYENNE BR 

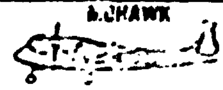
OBSERVATION SERIES

DESIGNATION	ENGINE	POPULAR NAME
O-1A	0-470-11B	BIRD DOG AK 
O-1D	0-470-15	
O-1E	0-470-11B	
O-1G	0-470-11B	

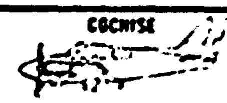
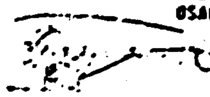
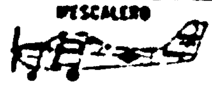
UTILITY SERIES

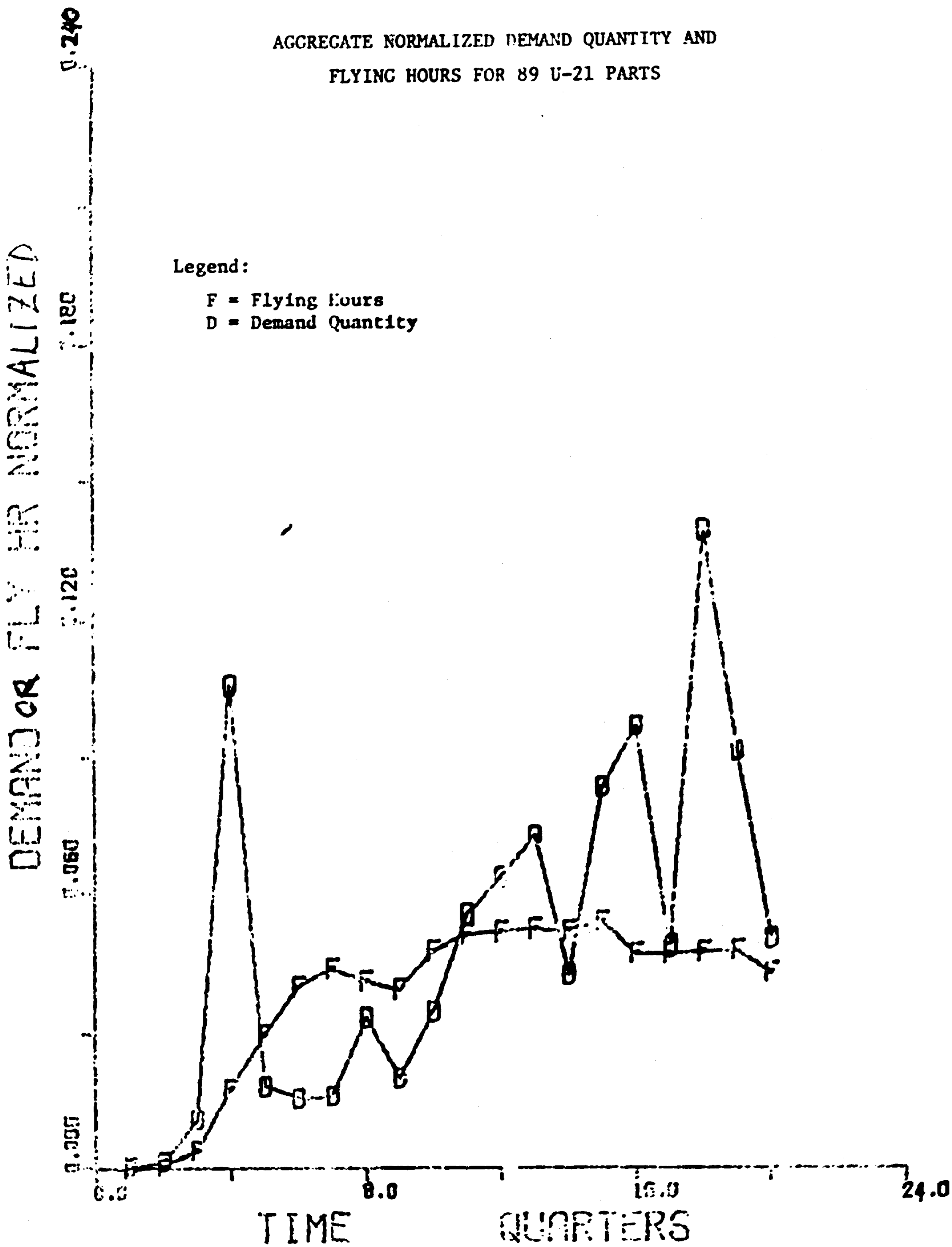
DESIGNATION	ENGINE	POPULAR NAME
U-1A	R 1340-61	OTTER AA 
U-6A	R-985-39A	BEAVER AB 
RU-6A	R-985-39A	
U-8D	0-480-1A	SEMINOLE AD 
RU-8D	0-480-1A	
U-8F	0-480-3	
U-8G	0-480-1A	
U-9B	0-435-G1C6	AERO COMMANDER AE 
U-9C	[illegible]	
[illegible]	[illegible]	
U-10A	0-480-C1D6	COURIER AF 
U-21A	T74-CP-700	UTE AG 

VTOL AND STOL SERIES

DESIGNATION	ENGINE	POPULAR NAME
OV-1A	T53-L-3,-7	MOHAWK AH 
OV-1B	T53-L-3,-7	
OV-1C	T53-L-3,-7	

TRAINER SERIES

DESIGNATION	ENGINE	POPULAR NAME
TH-13T	0-435-25A	SIOUX see OH-13
T-42A	IO-470-L	COCHISE AK 
TH-55A	HIO-360B1A	OSAGE BN 
T-41B	IO-360-D	MESCALERO AK 
TO-1D	0-470-11B	BIRD DOG AK 
O-1D	0-470-15	
O-1E	0-470-11B	



Note: See Appendix 2 for additional aircraft.

Best Available Copy

2.3 Input Data Editing

If an item was used on more than one aircraft TMS in a system, the quantity used per aircraft and the wearout rate were assumed to be similar on each aircraft. Consequently, for these items, the flying hours for all applicable aircraft in the system were simply added together. Parts applying to TMS models of different weapon systems were not included in this study.

Flying hour data were available only for US Army and Vietnam Air Force programs. Because of this limitation, processing was begun on a (voluminous) demand-transaction file with customers identified in order to remove demands from other military services and MAP countries. Some of the study results are based on a preliminary data base developed in this way from part of the detailed demand-transaction file. The eleven weapon systems each with acceptable data for at least 40 parts are marked with a dash in the weapon system table above. There are about 2000 items in this preliminary data base. It covers the 5-year period from January 1967 thru December 1971. The data were aggregated by weapon system as shown in the graphs. In developing the preliminary data base it was discovered that the non-Army demands were a small fraction of the total number. So the main part of the work was done with a larger data base which had already been aggregated to include all customers. (Only the customers were aggregated - not the items.) The advantages to be gained in using the larger data base were great enough to warrant the small risk that for a few individual items the non-Army demands might actually constitute the major part of their demand. The following table gives the number of parts (total 11631) by weapon system for the expanded data base.

DISTRIBUTION OF PARTS BY WEAPON SYSTEM IN AVSCOM 7-YEAR DATA BASE

AA	0	BA	599
AB	618	BC	0
AD	760	BD	981
AE	1	BE	0
AF	500	BF	3
AG	517	BG	875
AH	953	BH	434
AK	112	BJ	52
AL	0	BK	2719
		BL	712
		BN	877
		BP	701

The scope of this work was limited to recurring demand. When the demand was accumulated into quarters the following classes of requisition were not included:

initial issue,

mobilization and

rebuild

If the remaining demand was so small that there was not even one calendar year with at least four requisitions, the item was dropped. Such items are called <u>trivial-demand items</u> below.

The rest of this chapter applies only to the large data base used for the main part of the study. If there were no flying hours in the first two quarters (January to June 1967) the item was considered to be new to the system and was dropped (because it would likely be managed with maintenance factors in transition from provisioning.) Likewise an item for which there were no flying hours in the final two quarters (July to December 1973) was not included (because the item manager would have tempered any demand forecast with the knowledge that the aircraft was being phased out). Finally, items with over a million dollars of demand per year - see below for how estimated - were dropped because there are special forecasting methods for such parts. Each item was classified as low or medium dollar value (LDV) or high dollar value (HDV) according to whether the demand rate averaged over the full 28 quarters was less than or greater than or equal to $50,000; and the requisition rate was less than or greater than or equal to 100 per year.

To summarize, items were excluded for the following reasons:

38% managed by DISC or other NICP or not stocked

28% trivial demand

19% no way to associate with flying hours

2% applied to more than one system

1% new, phase-out or super high dollar items

This information is given in more detail in the "pipe" chart. Near the bottom of the chart is the legend "10509 GOOD ITEMS LEFT IN THE PIPE AT THIS POINT". The additional items removed below that point were dropped for two reasons. First, half of the LDV non-dynamic items (defined later) - including 18 P7% and 5157 stock fund - were dropped to reduce computer

DATA EDITING

Pipe Contains
88944 Items
in AVSCOM
Catalog
Dec 1971

33995 Items Not Managed by AVSCOM
or Not Repair Parts

24717 Items With Trivial Demand in 1967-1973

16727 Items For Which No Program Data Available

1835 Items Applied to More Than One Weapon System

1122 Items New in 1967 or Phase Out By 1973

39 Items With Annual Demand of More Than $1 Million

10509 Good Items Left in the Pipe at This Point

5186 LDV Non-Dynamic Items Not Used (Including 29 PEMA)

Pipe to Simulator Now Contains the Remaining 5323 Items

expense in the simulation runs. To compensate, we double weight the LDV non-dynamic results in the final tabulations. Then the remaining 11 PEMA items were also dropped. The reason this was done was because the PEMA items were such a tiny fraction of the LDV non-dynamics (29 out of 10350) that they were thought to be atypical. Usually PEMA items are expensive and reparable items; the LDV non-dynamic class was intended to contain relatively cheap non-reparables.

2.4 Final Characteristics of Data Base

The data base was separated into LDV and HDV portions as described above. Each of the portions was divided further into dynamic and non-dynamic portions. The criterion for this partition was the item's Federal Stock Class (FSC). The table below gives the fraction of items in the most important aircraft Federal Stock Classes. The upper part of the table contains the classes included in the definition of dynamic items. The important dynamic components were considered to be those that experience very high rotation rates; i.e., rotor blades, transmissions, turbine engines and other engine components. This encompassed about ten percent of the items (FSCs selected for us by AVSCOM to contain dynamic items are 1615, 2840 and 2810).

DISTRIBUTION OF ITEM FSC CLASS

PERCENT	FED. STK CLASS	DESCRIPTION (AR 708-15)
9	1615	Helicopter Rotor Blades and Drive Mechanisms (Transmissions)
1	2810/2840	Engines
10	TOTAL	Dynamic Items

39	1560	Airframe Structure
14	1680	Misc. Accessories
4	1650	Hydraulic, Vacuum and De-icing
3	2995	Engine Accessories
2	3120	Bearings, Plain, Unmounted
2	5340	Misc. Hardware
2	1620	Landing Gear
2	1660	Air Conditioning, Heating and Pressurizing
1	5330	Packing and Gasket Materials
21	Other	
90	TOTAL	Non-Dynamic Items

Notice that the nondynamic items include bearings and engine accessories some of which are likely to have dynamic characteristics. Thus this class may be contaminated. It was felt that it was more important to have an uncontaminated group of dynamic items than nondynamic in order to be able to draw certain conclusions about forecasting methods.

The final data base characteristics are shown in the following table. The major classes of items, with subtotals are given in the left hand column. The next column gives the total number of items in each class. The reason the total is 11631 here (and in the weapon system chart) instead of 10509 as in the "pipe" chart is because this table was made before the 1122 NEW AND PHASE-OUT items had been removed. The last two columns give the totals broken out by fund (PEMA or ASF) and segment (non-reparable, reparable or insurance item).

DATA BASE CHARACTERISTICS
DISTRIBUTION BY ITEM CHARACTERISTICS
FINAL ITEM SET IN SIMULATION

ITEM CLASS	TOTAL ITEM COUNT	PEMA	ASF	NON-REP	REP	INS
LDV Non-Dynamic	10350	29	10321	9877	448	25
LDV Dynamic	1008	24	984	957	51	
LDV TOTAL	11358	53	11305	10834	499	25
HDV Non-Dynamic	174	30	144	66	108	
HDV Dynamic	99	52	47	26	73	
HDV TOTAL	273	82	191	92	181	
TOTAL Non-Dynamic	10524	59	10465	9943	556	25
TOTAL Dynamic	1107	76	1031	983	124	
TOTAL Good Items	11631	135	11496	10926	680	25

CHAPTER III

MODEL DEVELOPMENT

We consider three simple alternative demand models:

1. Average demand is constant.
2. Average demand is proportional to total flying hours.
3. Average demand has a component described by Model 1 and a component described by Model 2.

In none of these three models is the demand to be any different from failures of parts at the user level. However, in the fourth model below, we implicitly allow for the delay due to stockage at supply levels between the original failure and the final demand at the NICP level.

4. Failures are proportional to total operating hours; a demand is delayed from the time of the failure by an unknown amount.

In all four models the word "constant" means a value that may change gradually but does not depend on demand or program. The forecasting algorithms to be tested are based on these models. They are grouped under the appropriate model following the definition of the notation.

Notation

Subscripts represent time as follows:

Small letters stand for quarters, large letters stand for several contiguous quarters. Time periods are always relative to the present; the forecast is being computed as of the end of quarter 0. There are B quarters in the base period and P quarters in the forecast period.

Base period:

$$D_B = \sum_{q=-(B-1)}^{0} D_q$$ where D_q is the actual demand in the qth quarter

$$F_B = \sum_{q=-(B-1)}^{0} F_q$$ where F_q is the program data value (flying hours) in the qth quarter

Forecast period:

$$F_p = \sum_{q=1}^{P} F_q$$

$$_A D_P = \sum_{q=1}^{P} D_q$$

This is the final forecast for algorithm A. D_q is the estimate given by algorithm A for the demand in the qth quarter.

In the following descriptions of the algorithms any unspecified sums are intended to be over the base period.

Model 1

Demand is constant.

MOVAVG Algorithm (moving average)

$$D_P = (\frac{P}{B})\ D_B$$

Comment:

The "constant" demand rate is estimated as the mean of recent observations.

TREXPF Algorithm (triple exponential smoothing)

$$D_p = \sum_{q=1}^{p} \hat{D}_q$$

where

$$D_q = a_t + b_t q + \frac{1}{2} c_t q^2$$

$$a_t = D_o + (1-\gamma)^3 \; (D'_{t-1} - D_o)$$

$$b_t = b_{t-1} + c_{t-1} - \frac{3}{2}\gamma^2 (2-\gamma)(D'_{t-1} - D_o)$$

$$c_t = c_{t-1} - \gamma^3 \; (D'_{t-1} - D_o)$$

$$D'_t = a_t + b_t + \frac{1}{2} c_t$$

and γ is the fixed smoothing constant.

Comment:

The t index represents the absolute quarter; the q index is for the quarter relative to the present. Thus D_o is the actual demand in the quarter just ended.

The a, b, c initial values are developed from a least square linear regression on the 3 earliest available quarters of demand. The initial value of $\hat{D}_o$ is set equal to this initial a-value unless an estimate is available.

The algorithm was tried with the following values of γ to give four separate estimates of demand:

$$\gamma = .05, .1, .15, .19$$

In this algorithm the gradual changes in the "constant" demand rate are given explicit recognition in the trend estimators b and c.

Reference: Robert Goodell Brown, Smoothing Forecasting and Prediction of Discrete Time Series, Prentice-Hall 1963, Chapter 9.

Model 2

Demand is proportional to total flying hours.

SEV94 Algorithm (issue interval)

$$D_P = \left(\frac{F_P}{F_B}\right) D_B$$

Comment:

In this form it is viewed as a moving average corrected by a program factor. It may also be written:

$$D_P = \left(\frac{D_B}{F_B}\right) F_P$$

In this equivalent form it is seen to be a relationship between demand and program data like the following algorithm.

REGORG Algorithm (Slope linear regression)

$$D_P = b\ F_P$$

where

$$b = \frac{\Sigma D_q F_q}{\Sigma F_q^2}$$

Comment:

Notice that both the REGORG and SEV94 algorithms are special cases of the form:

$$D_p = \frac{\Sigma w(q) D_q}{\Sigma w(q) F_q} \ F_p$$

where the weight function w is constant in the SEV94, but is variable in the REGORG and equal to F_q. Thus, in the SEV94 algorithm each quarter is given weight, in the REGORG algorithm each flying hour is given equal weight.

SBASEM Algorithm (sliding base period)

$$D_p = \sum_{q=1}^{p} D'_q$$

$$D'_q = \frac{\sum_{i=q-B}^{q-1} D''_i}{\sum_{i=q-B}^{q-1} F_i} F_q$$

where

$$D''_i = \begin{cases} D'_i & \text{if } i > o \\ D_i & \text{if } i \leq o \end{cases}$$

Comment:

This algorithm is similar to the SEV94 algorithm. The difference is that each successive quarter in the forecast period is forecast using a base period which ends with the previous quarter. For all except the first quarter this means that forecasted demand appears in this base period. This results in more weight being given to recent quarters than to earlier quarters of the real base period in any forecast for more than one quarter in the future.

Model 3

Demand is partly constant and partly proportional to operating hours.

PARTEF Algorithm (partial effect)

$$D_p = (\gamma)({}_{SEV94}D_p) + (1 - \gamma)({}_{AVGMOV}D_p)$$

where γ is a constant.

Comment:

This is a weighted mean of two simple estimates described above.

γ is intended to be fixed, but possibly re-evaluated from time to time, and will be the same for all items.

The algorithm was tested with the following values to give four separate estimates of demand:

$$\gamma = .25, .5, .75, .95$$

THRESH Algorithm (program factor only if a discriminant function reaches a threshold value)

$$D_p = (B)({}_{REGORC}D_P) + (1-B)({}_{AVGMOV}D_P)$$

where

B is 0 or 1 as determined by the following test:

Let $t = \dfrac{b}{\dfrac{s}{\sqrt{\Sigma F_q^2}}}$

s is an estimate of the standard deviation of the error in the fitted line:

$$D_q = b\,F_q$$

$$s = \sqrt{\dfrac{\Sigma D_q^2 - \dfrac{\Sigma D_q^2 F_q}{\Sigma F_q^2}}{df}}$$

and df = Base Period - 1.

Then $B = \begin{cases} 1 \text{ if } t \geq tdf \\ 0 \text{ otherwise} \end{cases}$ where $tdf = \begin{cases} 2.35 \text{ if } df = 3 \\ 1.89 \text{ if } df = 7 \\ 1.80 \text{ if } df = 11 \end{cases}$

Comment:

This algorithm is a heuristic that determines whether the flying hours and demand are closely-enough related in the base period to warrant using the REGORC forecast. If t is too small the algorithm falls back on the moving average.

PARTRG Algorithm (PARTEF with variable parameter)

$$D_P = b\,({}_{SEV94}D_P) + (1-b)({}_{AVGMOV}D_P)$$

where b is variable.

$$\text{Error} = \left|\frac{\hat{D}_{P'} - D_{P'}}{\max(1, D_{P'})}\right|$$

where $D_{P'} = \sum_{q=-(P'-1)}^{0} D_q$

and $\hat{D}_{P'} = b\left(\frac{P'}{B'}\right) + (1-b)\,\frac{F_{P'}}{F_{B'}}\quad D_{B'}$

and $B' = P' = \frac{B}{2}$

Comment:

The parameter b is determined as the value in range [0,.05,.1,...1.0] which minimizes the error in forecasting the second half of the base period using the first half as a base. If the error > .4 b is set to 0.

REGINT Algorithm (Slope, Intercept linear regression)

$$D_P = a + b\,F_P$$

where $a = \left(\frac{P}{B}\right)(D_B - b\,F_B)$

$$b = \frac{\Sigma\left(F_q - \frac{F_B}{B}\right)\left(D_q - \frac{D_B}{B}\right)}{\Sigma\left(F_q - \frac{F_B}{B}\right)^2}$$

Comment:

Note that the PARTEF algorithm reduces to the REGINT if we make the following substitution:

$\gamma = b\,\left(\frac{F_B}{D_B}\right)$ instead of using a fixed value.

POWERF Algorithm (fixed power)

$$D_P = \left[\frac{\frac{F_P}{P}}{\frac{F_B}{B}}\right]^{\gamma} \text{AVGMOV } D_P \qquad 0 \leq \gamma \leq 1$$

where γ is fixed.

Comment:

In POWERF, γ is used in the sam way that it is in the PARTEF algorithm. This algorithm has a compromise character like the PARTEF, but its form is non-linear. The parameter γ determines the fraction of the rate of change of flying hours by which the demand forecast will change.

POWREG Algorithm (variable power)

$$D_P = \sum_{q=1}^{P} D_q$$

where:

$$D_q = \left[\frac{F_q}{\frac{F_B}{B}} \right]^b \frac{1}{P} \left(AVGMOV \, D_P \right)$$

and $$b = \frac{\Sigma XY}{\Sigma X^2} \quad \text{constrained to } -10^{10} \le b \le 1$$

where $$Y = \log \frac{D_q}{\frac{D_B}{B}}$$

$$X = \log \frac{F_q}{\frac{F_B}{B}}$$

Comment:

This algorithm was developed by linear regression on the logarithm of the power form. Note, in the formula for b, if either X or Y is undefined for a quarter, that quarter is excluded from the sums in both numerator and denominator.

Model 4

Failures are proportional to total operating hours; a demand is delayed from the time of the failure to allow for the effect of stockage at intermediate supply points.

To test this model, each of the algorithms that made use of program data were tested with

$$F_q \text{ replaced by } F_{q-K}$$

where the three values 1, 2 and 3 quarters were tried for the lag K.

EXAMPLE OF APPLICATION OF SOME OF THE FORECAST ALGORITHMS

HYPOTHETICAL DEMAND AND FLYING HOUR DATA

QUARTER	DEMAND	FLYING HOURS
Jun 67	12	230
Sep 67	0	245
Dec 67	0	271
Mar 68	3	270
Jun 68	1	250
Sep 68	5	220
Dec 68	0	200
Mar 69	8	190
END OF 2-YR BASE PERIOD		
Jun 69		185
Sep 69		187
Dec 69		180
Mar 70		160
END OF 1-YR FORECAST PERIOD		

FORECASTED DEMAND

ALGORITHM	FORECAST	ALGORITHM	FORECAST
MOVAVG & PARTRG	14.50	REGINT	27.34
SEV94	11.01	SBASEM	9.40
PARTEF.5	12.75	POWREG	51.10
THRESH & REGORG	10.27	TREXP.05	1324.73
POWERF.5	12.63		

CHAPTER IV

MODEL VALIDATION AND SELECTION

4.1 Screening

The method by which the final selection of the best algorithm was made is described in the next section. In this section is detailed how the algorithms described in the preceding chapter were first screened to reduce them to a small enough number so as to be economically compared by simulation.

It was originally supposed that most of the algorithms would do poorly compared to a few good ones. However, as shown in the chapter on Results, most of the algorithms performed about the same in screening.

The screening criterion was sufficiently different from that of the simulation to give additional confidence in an algorithm which did well in both. Since many algorithms performed similarly in screening, the selection of algorithms for final comparsion was somewhat subjective. The moving average algorithm (MOVAVG) was included as a control in order to determine whether the use of a program factor had any value at all. (Since aggregate demand followed the program data so closely, as can be seen in the graphs in the Data chapter, it seemed likely that individual item demand would also.)

In addition, the Army's presently used forecasting algorithm (SEV94) had to be included in the final testing so that its relative value, as compared to other algorithms, could be assessed.

It was decided to include only two more algorithms so that the available computer funds could be spent in more intensive testing, i.e., more items in the data base.

The screening process will now be described in detail. The data was first aggregated by weapon system. Equal weight was given to each item independently of its cost. This was done by normalizing the demand so that the relative quarter-to-quarter variations counted equally for different items. The normalized value for quarter q is:

$$\frac{D_q}{\sum_{q=1}^{20} D_q} \quad \text{for each item.}$$

Then, this quarterly value was averaged over all the items in the weapon system. The example should make this normalizing process clear.

NORMALIZATION EXAMPLE

(FOR CLARITY 6-MONTH PERIODS ARE SHOWN INSTEAD OF QUARTERS)

YEAR	1967		1968		1969		1970		1971		TOTAL
ITEM	0	0	1	1	5	4	2	2	5	0	20
1	0	0	.05	.05	.25	.2	.1	.1	.25	0	1
ITEM	0	0	6	6	30	24	12	12	30	0	120
2	0	0	.05	.05	.25	.2	.1	.1	.25	0	1
ITEM	0	4	3	0	0	1	0	0	2	0	10
3	0	.4	.3	0	0	.1	0	0	.2	0	1
NORMALIZED AGGREGATE	0	.133	.133	.033	.167	.167	.067	.067	.233	0	

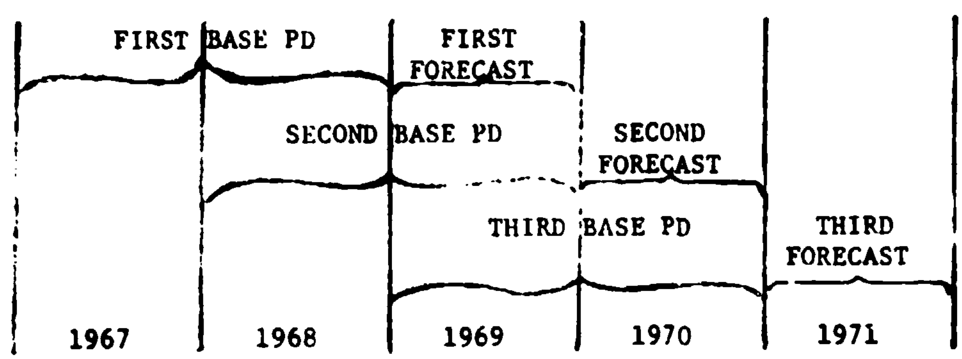
FOR EACH ITEM THE UPPER LINE IS THE ACTUAL DEMAND,
THE LOWER IS THE NORMALIZED VALUE

In the example, items 1 and 2 have exactly the same quarter-to-quarter variations even though their demand totals are quite different. The third item shows much more variation than the first two. Notice that the final aggregate tends to be smoother than the individual items. Because of this an algorithm that does well in the screening might do poorly in the final selection when individual items are used. This should be especially true

of an algorithm like triple exponential smoothing, which responds radically to sudden changes.

The forecast-error criterion is used merely as a screening method. Final selection is based on economic considerations to be described below. The measure of forecast error employed in the screening phase is the mean absolute value (MAD). The MAD was used rather than a squared measure so as not to overemphasize large errors.

The testing procedure was designed to yield the greatest number of forecasts while avoiding overlapped forecast periods. An example will help to explain this procedure. Assume we are testing with a two-year base period and a one-year forecast period. The base period for the first forecast will cover the first two years, and the first forecast period will immediately follow the end of this base period. After the forecast is compared to the actual demand in the forecast period, and the resulting error saved, the process is repeated for the next forecast period. To do this the base and forecast periods are shifted forward by the length of the forecast period (one year in the example).



As can be seen there are three forecasts, and thus three values of MAD, for the case of a two-year base period and a one-year forecast period. For screening, three different forecast period lengths (.5, 1 and 1.5 years) were employed and the results averaged. The table gives the number of MADs for each forecast period length for each of two base period lengths studied.

TOTAL FORECAST MADs FOR EACH WEAPON SYSTEM

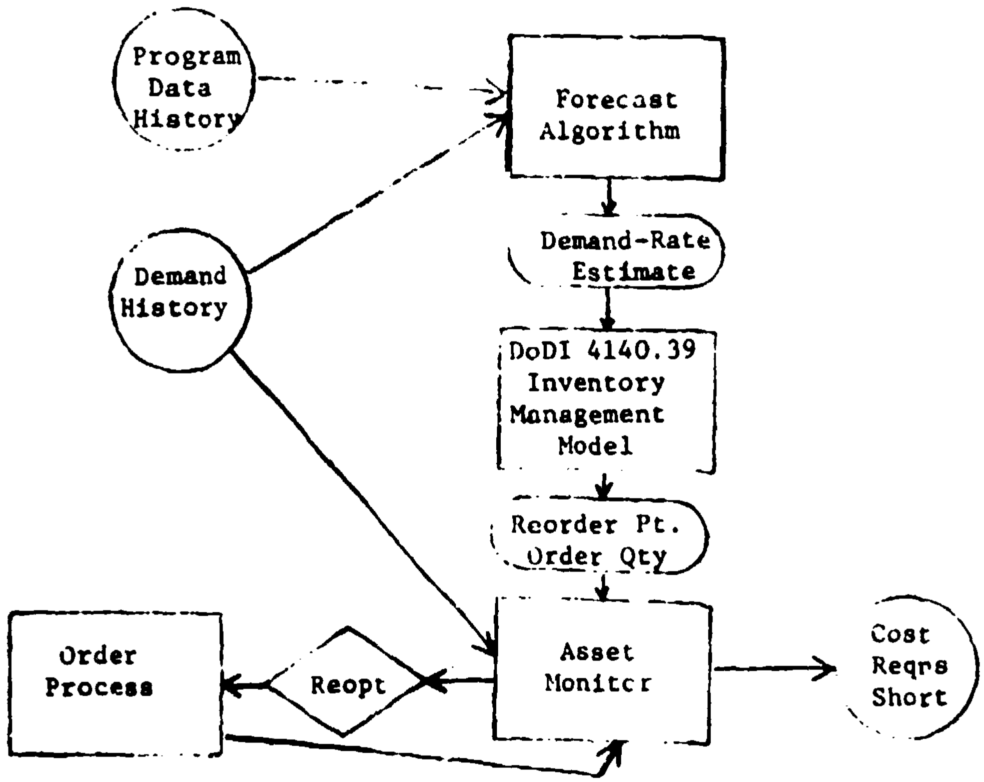
BASE PERIOD	FORECAST PERIOD .5 YRS	1 YEAR	1.5 YRS	TOTAL FOR BASE PERIOD
2 YRS	6	3	2	11
3 YRS	4	2	1	7

In comparing the algorithms for a 2-year base all eleven forecast results could be used. However, to compare base periods, only 7 could be used because, to be strictly comparable, the forecasts must cover the same time period; and the year 1969 is excluded as a forecast for the 3-year base period. A similar remark applies to testing the effects of lag; in this case nine forecasts were available since the maximum lag was 2 quarters.

4.2 Simulator Overview

The final selection among algorithms was made by observing their operation in the Army's NICP context using the DoDI 4140.39 simulator. This simulator is described in the report "ALPHA 4140.39 Simulator" by Martin Cohen (May 1973) AD 762348. Some changes were made to the simulator since the report was published; the major changes are listed in Appendix 1.

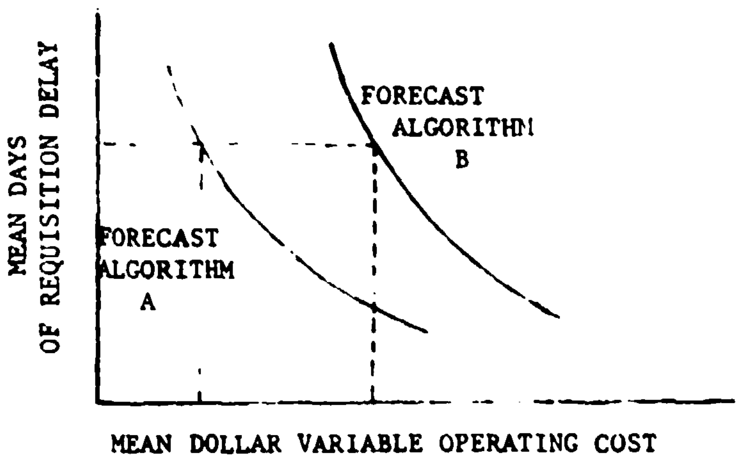
The general organization of the simulator is given in the chart, which shows the flow of information among the processes.



ALPHA 4140.39 SIMULATOR ORGANIZATION

The demand history for a given item is fed both to the forecast algorithm process, which computes the demand forecast for each period; and to the asset monitor, which reduces on-hand stock - thus possibly triggering an order for replenishment - and computes the final performance estimates. The demand forecasts are fed to the inventory model, which computes the reorder point needed for asset monitoring and the order quantity needed when orders are placed. The final performance estimates are averaged over the simulated time for each item, and then aggregated across all items. This is done separately for each forecasting algorithm. The resulting values are compared to determine the best one.

The results of the simulation runs appear in the next chapter in the form of graphs of performance versus cost. A typical graph looks like this.



The curves are traced thru several points for each algorithm; each point results from a run of the simulator with another value of the lambda parameter. (See the Simulator report or the report by Deemer and Kruse cited in Appendix 1.) In the above hypothetical graph, Algorithm A is seen to be superior to Algorithm B because it incurs a lower cost for the same performance.

CHAPTER V

RESULTS

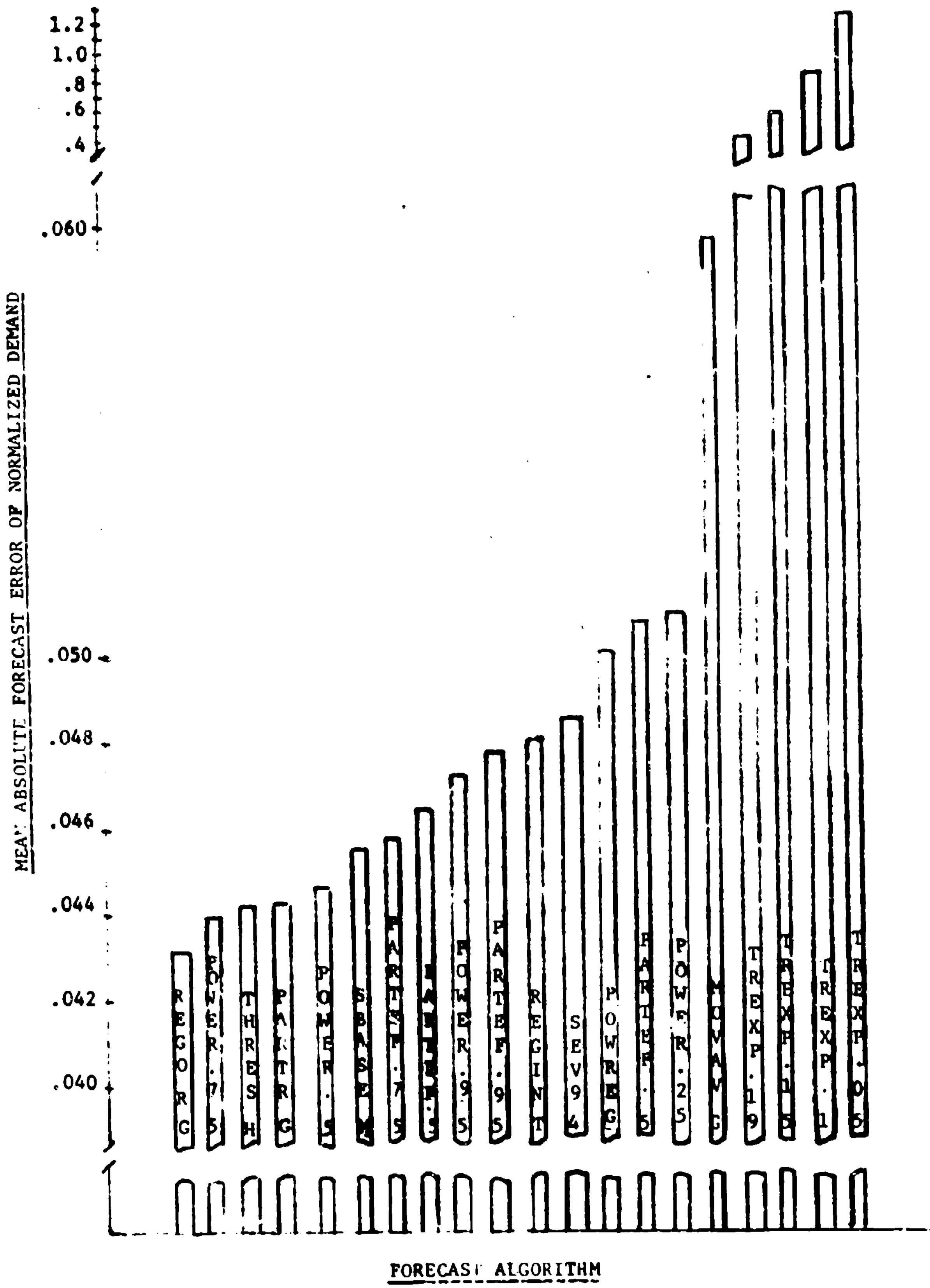
5.1 Algorithm Selection

The results of screening are shown on the bar graph. Recall from section 4.1 that the criterion for comparing algorithms is mean absolute deviation of the forecast from the actual demand (MAD). This MAD is the mean of 121 samples (two-year base period with forecasts for 6 months, one year and 18 months - 11 forecasts for each of 11 aircraft systems). The best algorithm has a MAD of .043; since the expected value of the forecast is .16, this is a relative error (PCER) of 26%.

Notice that the difference between the best and worst algorithms that utilize program data is about the same as the difference between the worst and the moving average (which does not use program data).

ALGORITHMS RANKED BY SCREENING

EXPECTED VALUE OF NORMALIZED DEMAND = .16



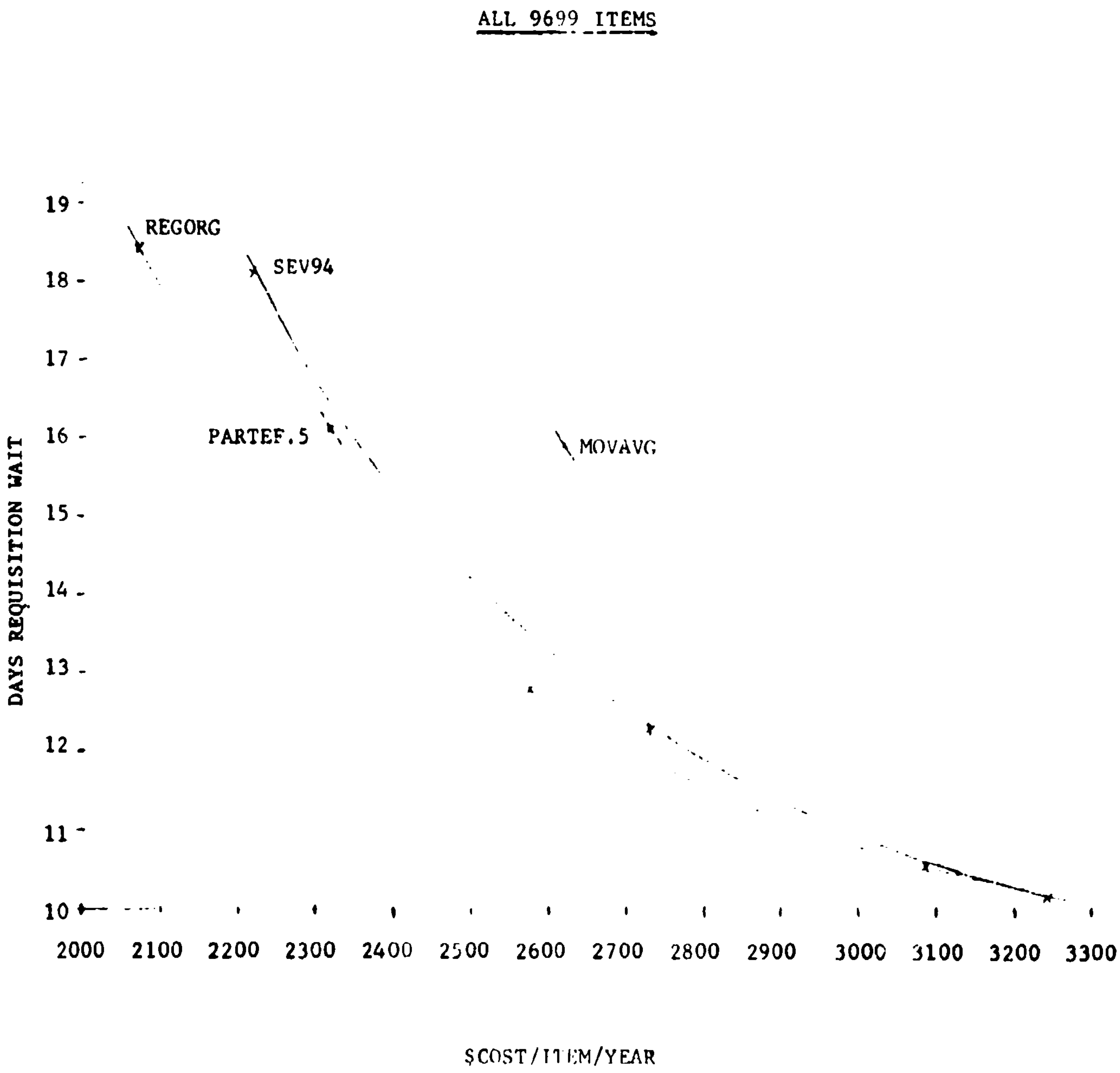
The regression-of-slope algorithm (REGORG) had the smallest MAD and thus was selected to be included in the final testing phase. The partial-effect algorithm with various values of the paramenter did not do consistently well. However, it did perform well in a study on rifle parts [GAJDALO 1969]. It was decided to include this algorithm (PARTEF) with a parameter of .5 so as to be as different as possible from the extremes of SEV94 and MOVAVG also included. Thus four algorithms were submitted for final testing with the Simulator.

5.2 Simulation Results

In section 4.2 it is stated that the results of simulating each algorithm are displayed as a curve on a graph of average requistion delay (due to stockouts) versus total variable operating cost. The curve for the best algorithm will be to the left of those for all the others, indicating the lowest cost for a given delay time.

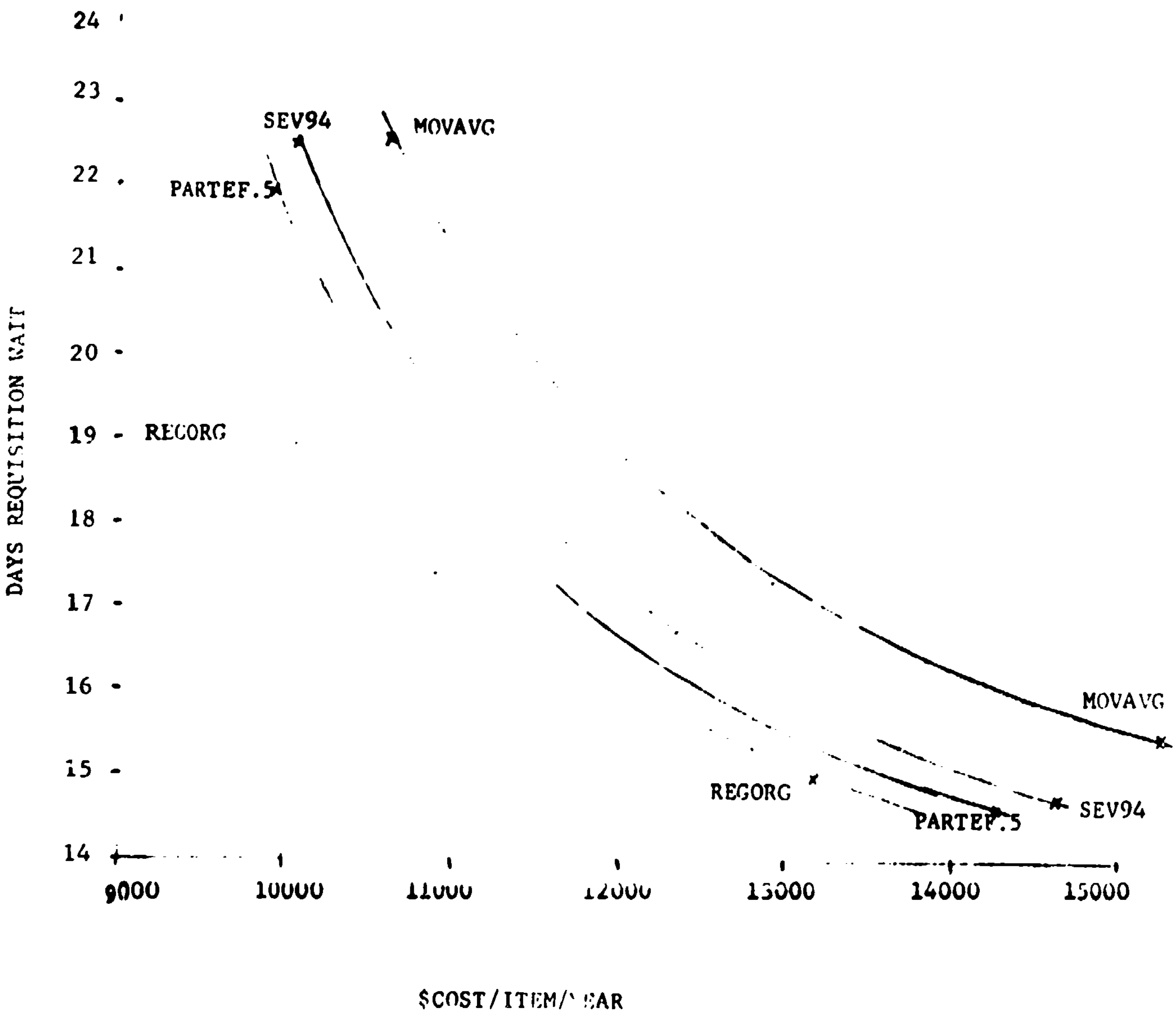
The first graph shows the results for the simulation run of all items. On this graph it can be seen that the SEV94 algorithm is much better than a simple moving average (MOVAVG). The PARTEF algorithm performed about as well as SEV94. REGORG, however, averaged $130 per year per item cheaper than SEV94 for the current 17-day mean requistion delay. This is a saving of over 5% or more than one million dollars per year. It can be seen that the ranking of the algorithms studied in the Simulation is essentially the same as it was in the screening phase.

When we consider just the dynamic items in the next graph, we see that the results are similar to those for all items together, except that now the differences between algorithms are more pronounced. For this group of items PARTEF is noticeably better than SEV94, but REGORG is still the best.



ALL 9699 ITEMS
DAYS REQUISITION WAIT
19
18
17
16
15
14
13
12
11
10
REGORG
SEV94
PARTEF.5
MOVAVG
2000
2100
2200
2300
2400
2500
2600
2700
2800
2900
3000
3100
3200
3300
$COST/ITEM/YEAR

796 DYNAMIC ITEMS



The last graph shows the results for the rest of the items. Again the algorithms that utilize program data (REFORG, PARTEF, and SEV94) appear to be superior to the one that doesn't (MOVAVG). However, it cannot be definitely proven from these results whether program factors are really more effective than simple demand history forecasting algorithms for nondynamic items because of the contamination with items that are possible dynamic. What can be determined is that there is much less difference among the various program factor algorithms for this group of items than for the dynamic items.

Caution must be exercised in using these graphs. While there is considerable safety in using them to rank the algorithms, there is much less assurance that the actual cost values are correct. Evaluation of these costs is beyond the scope of the present work.

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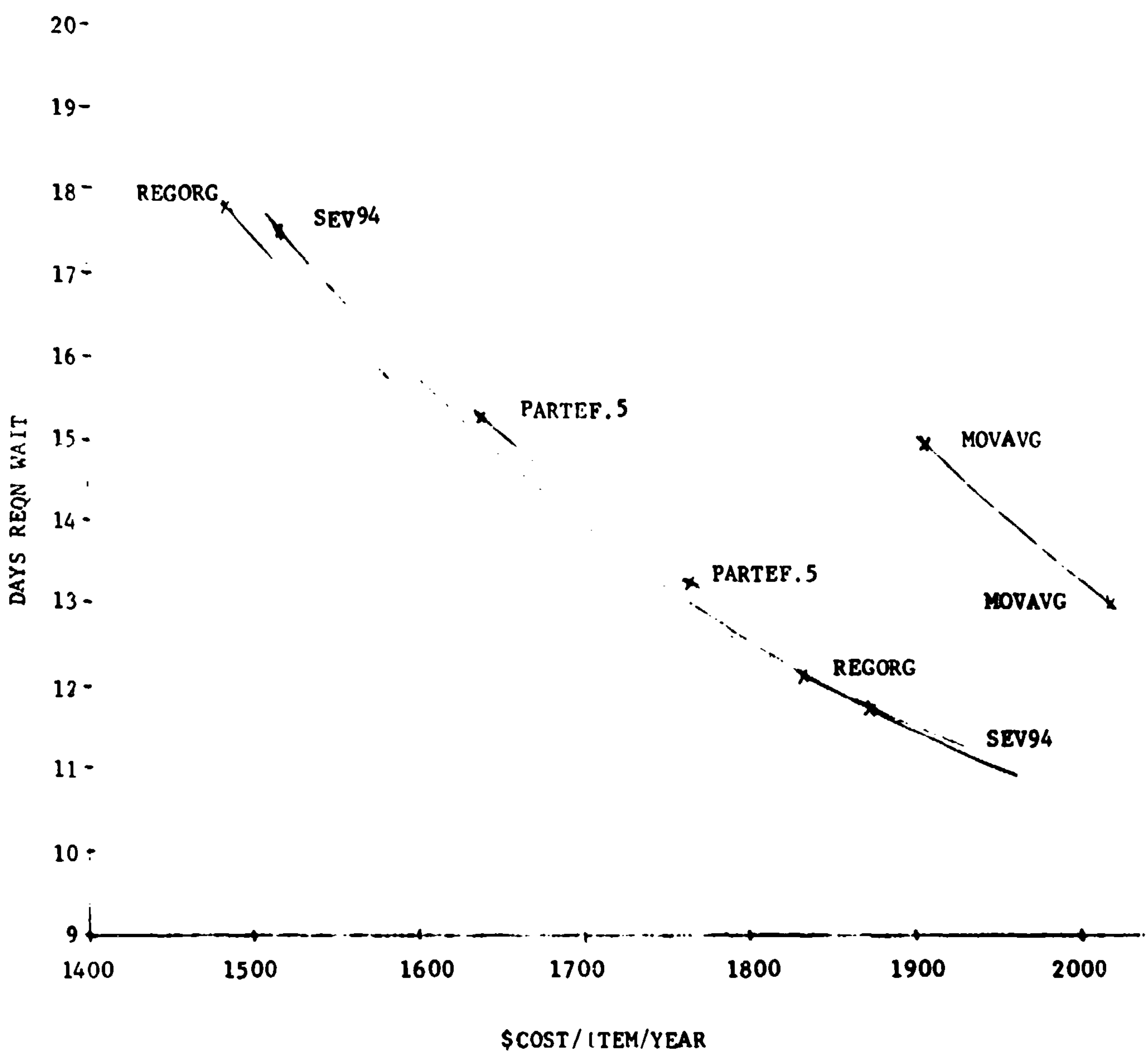
NONDYNAMIC ITEMS

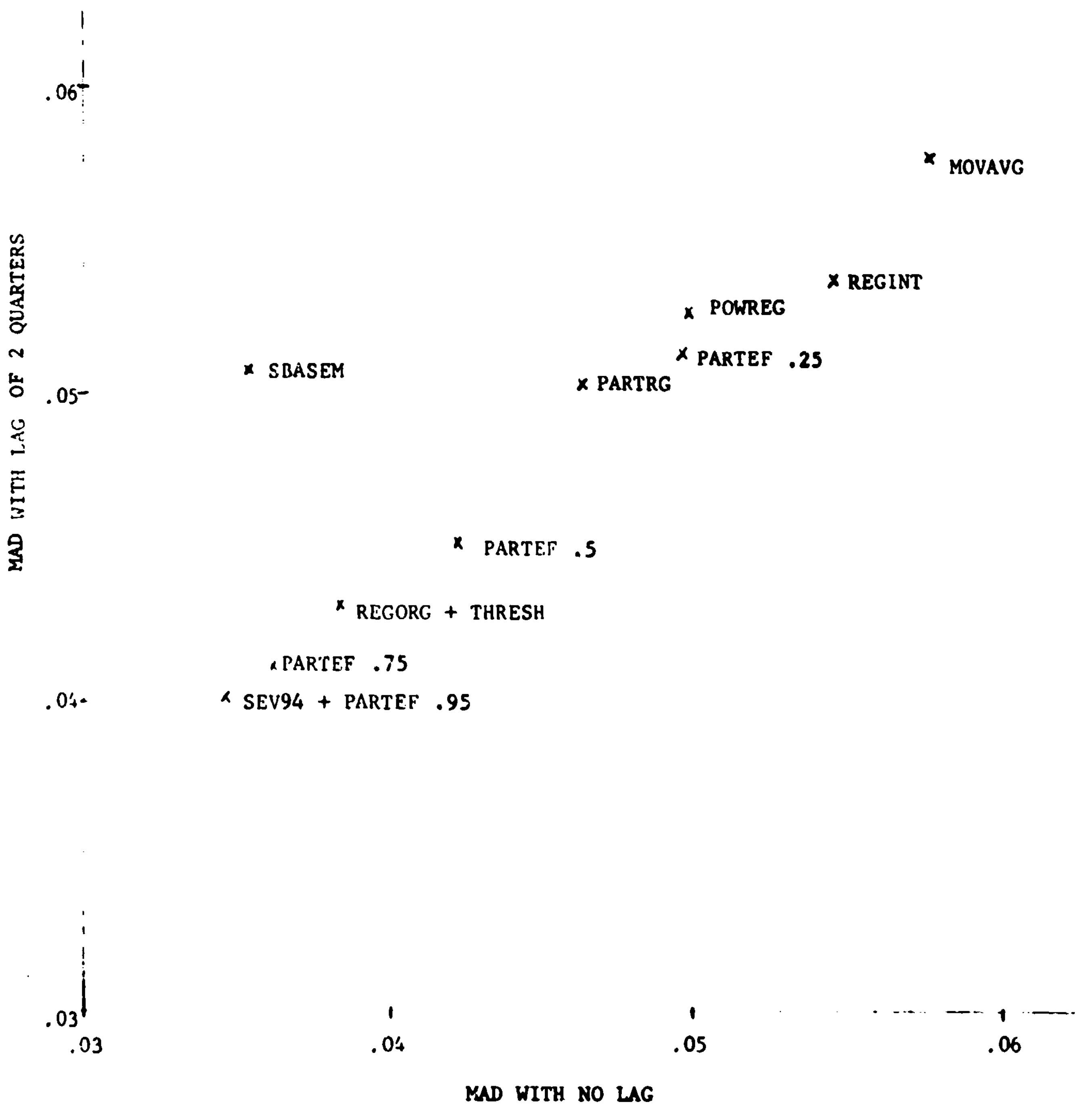


5.3 Lag, Base Period and Stratification

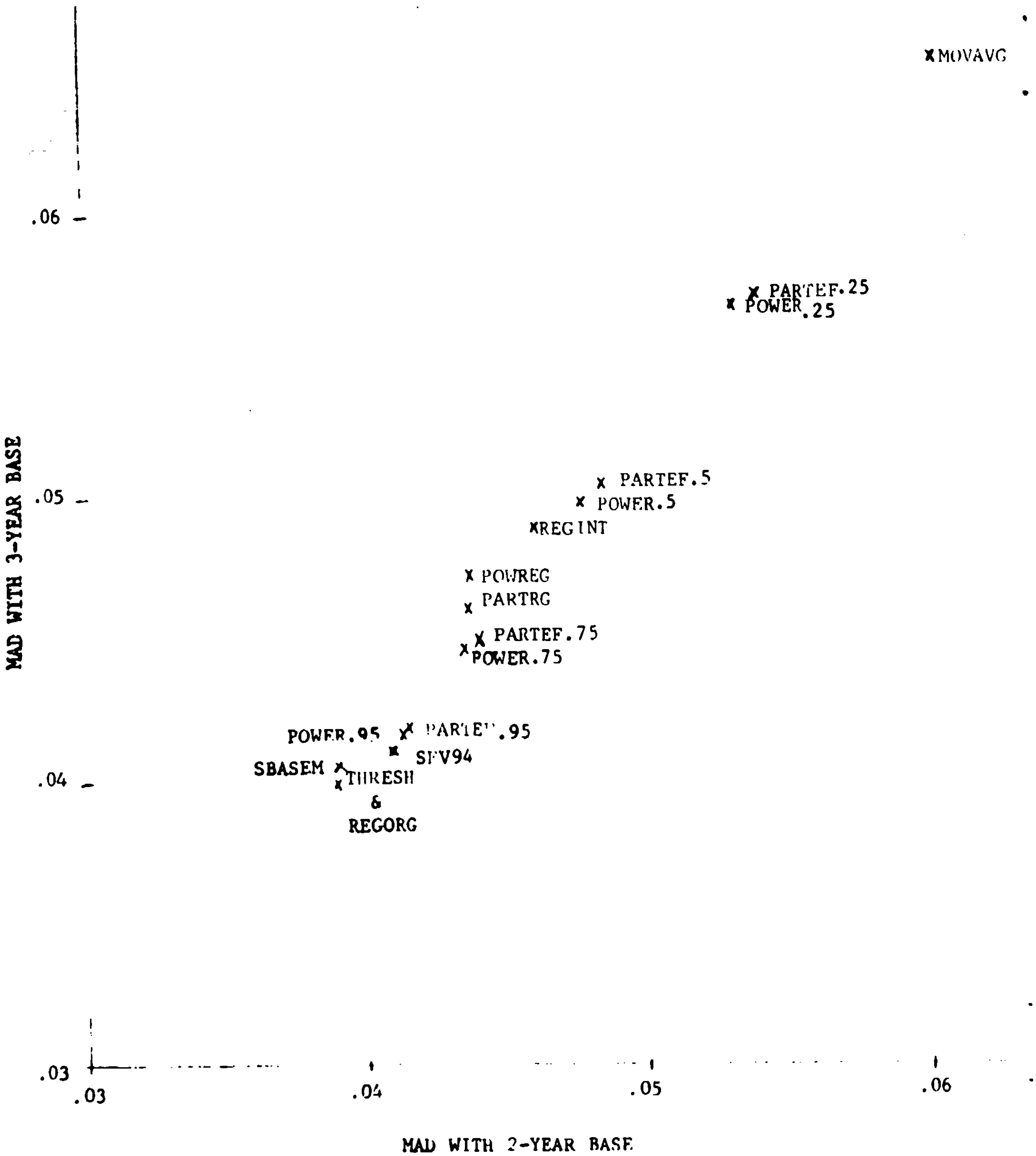
The final three graphs give the results of the study to determine the effects of these modifications to the forecast algorithms: lag (Model 4), increased base period, and a stratification of the items into low and high demand (not dollar value) classes. This work was done with the technique used for screening; thus rankings of many algorithms are compared. On each graph is plotted the mean absolute forecast error with the proposed modification versus that without it.

An examination of the three graphs suggests the following conclusions. A two-quarter lag degrades forecasting by most algorithms, as does a 3-year base period. The demand-rate stratification has no overall effect. Stratifications were also attempted on unit price and demand dollar value with no effect. These are not shown here.

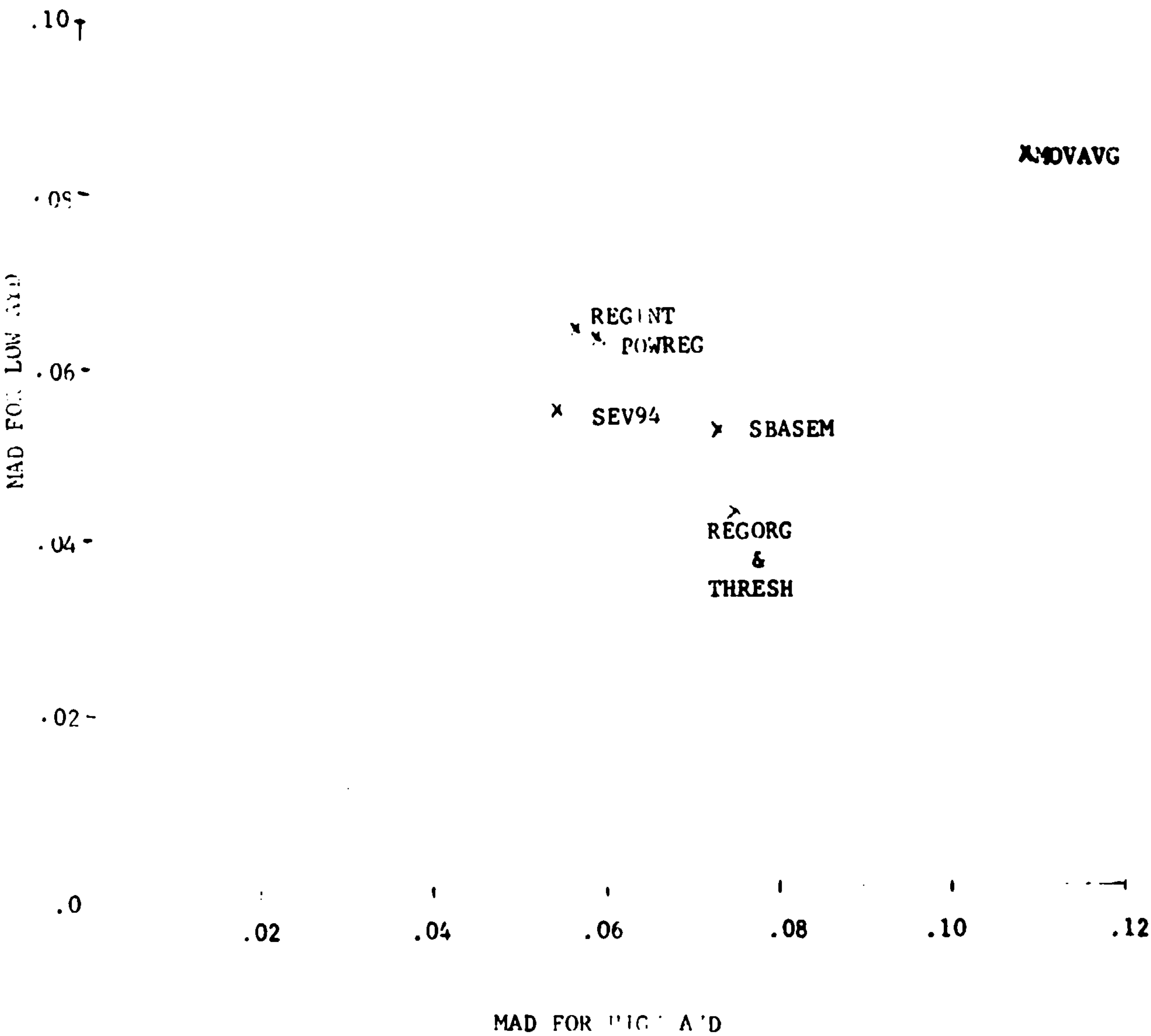
EFFECT OF LAG



EFFECT OF BASE PERIOD



EFFECT OF AVERAGE DEMAND



The negative result for the longer base period can be challenged because the advantage of the longer base period (smoothing out the demand) was anticipated by the aggregation into weapon systems. Work by the Air Force Logistics Command suggests that longer base periods are more effective with a moving-average forecast. While this does not seem likely with the Army's data, because of the trends present, a longer base period may well improve the forecasts developed with a program factor. AMCIRO is examining this possibility in a different project.

5.4 Final Conclusion

The Army's present program factor is better than a simple moving average.

Regression on an eight-quarter base period to determine the relationship between demand and program (assuming proportionality) is better than the present forecasting method.

The savings on a limited group of dynamic items using the regression algorithm are so large that this algorithm can be used in forecasting all items, thus avoiding the use of separate algorithms for different groups of items. In fact isolation of dynamic items from the non-dynamic was not complete enough to permit determination of a forecasting algorithm preferred for each group separately; nor does it seem to be cost effective to try to find separate algorithms because of the small economic impact of the non-dynamic items.

Lagging the demand as much as two quarters does not improve forecasting.

No method was found for classifying items based on unit price, average demand rate or dollar value of demand such that different forecasting algorithms would be preferred for different groups of items.

APPENDIX 1

CHANGES TO SIMULATOR FOR PROGRAM FACTOR PROJECT

PREFACE

The simulator used for final selection of the forecasting algorithm is described in the report, "ALPHA 4140.39 Simulator" May 1973 by Martin Cohen (AD 762348). Changes to adapt it to the present application, for general improvements and to correct errors, are described here and keyed to section headings in the simulator report and to the figure in the Model Validation and Selection chapter of this report.

Most of the changes were made in order to be consistent with the recommendations for CCSS in the report, "Evaluation of Several VSL/EOQ Models," by Robert L. Deemer and W. Karl Kruse, May 1974, AD 781948.

INVENTORY DECISION PARAMETERS (SECTION . .4) - DODI 4140.39 INVENTORY MANAGEMENT MODEL

REORDER POINT

Instead of using the model III safety level as defined in "More Ado About EOQ" by V. J. Presutti and R. Trepp in NRLQ 17, 12, June 1970, we are now using model IV. In this formulation the holding cost is proportional to the sum of on-hand plus on-order stock. The only change is to delete the holding cost rate, C_h, from the denominator of formula (2) on page 19 of the Simulator report.

Another change relates to the distribution assumed for the underlying demand process. When the lead time demand forecast is greater than 20 units Presutti's Laplace is used as before. However, when it is less than or equal to 20, the negative binomial is used. The theory is explained in Deemer and Kruse's May 1974 report. An approximation is used for the negative binomial; it is based on the Camp-Paulson approximation described in a paper by J.J. Bartko, "Approximating the Negative Binomial," in Technometrics 8,2, 1966. See "Application of Negative Binomial to Inventory Control," by R.L. Deemer, A.J. Kaplan and W.K. Kruse, December 1974, AD A003225, pages 9-12 for the details.

The variance estimation formula has also been changed to agree with recent work. It is now based on an empirical study with AVSCOM demand data, "Estimation of Demand Variability Parameters" by Alan J. Kaplan, May 1974, AD 781942. The final tables and formulas are given in Deemer and Kruse's May 1974 report.

REORDER QUANTITY

Formula (1) for Q on page 14 is still correct; however, there are two changes in the way the final quantity ordered is found.

First, the boundary value is no longer considered as an alternative to the result of the formula for Q. This means that the so-called boundary optimization has been abandoned. The second change is that the actual quantity ordered includes the reorder point deficit, the amount by which the assets were below the reorder point when the buy was triggered. Thus the policy is now to order up to the sum of the reorder point and order

quantity, which is more in line with actual practice and with the assumptions on which the inventory model is based.

Boundary optimization has been abandoned because now the actual quantity ordered includes the deficit, which would bring it above the boundary at which it was set to minimize cost. Rather than adopt a more complicated procedure to try to save a questionable policy like boundary optimization, the whole idea has been dropped under CCSS.

To summarize the changes in the reorder quantity, the former policy (pages 17 and 18 of the May 1973 report) was to find the smallest feasible reorder quantity that minimized the projected inventory related variable cost, and to order exactly that quantity (except when the deficit was too large, in which case a multiple of that quantity was ordered). The new policy is to order the deficit as well as the order quantity and not attempt to minimize the projected cost (except the minimization implied in the Q formula itself) by considering the Q value at the order cost boundary.

FREQUENCY OF RECOMPUTATION OF REORDER POINT AND QUANTITY

On page 13 of the Simulator report it is stated that the reorder point and reorder quantity are recomputed each time the reorder point is crossed as well as once a year for LDV items and monthly for MDV/HDV items. This has been changed with the installation of a "buy-back" policy. Now computations are not made when the reorder point is crossed, and the recomputation frequencies have been changed to semi-annually for LDV items and quarterly for MDV/HDV items. Also, reparable items are now considered to be MDV/HDV items, and the item's class (LDV or MDV/HDV) is now determined each time the decision is to be made, using the current value of the demand forecast. The buy-back policy assumes a 15 day reduction in procurement lead time; this has been implemented in the simulation except in the case that a buy actually occurs at the same time as a recomputation. For more information see "Frequency of Requirements Determination" by Robert L. Deemer, October 1974, AD A003227.

ZERO DEMAND FORECAST

On page 18 of the Simulator report it is stated that the safety level component of the reorder point is set to zero and the reorder quantity is set to one if the demand rate or variance forecast is zero. This has been changed because it may be very unrealistic for LDV items. Now, the number of months in the safety level and reorder quantity are calculated with forecasts that are not permitted to be less than one-third unit. The number of units in these levels are then calculated by multiplying the number of months times the demand rate forecast (which may be less than one-third unit per year or one-thirty-sixth unit per month). Whenever this is done the resulting reorder quantity is forced to be at least one unit; this is done to avoid placing several orders for a fractional number of units.

INITIALIZATION AND WARMUP (SECTION 2.5)

Before simulating each item an initial demand forecast is made and start-up values are computed. Then the item is simulated for some time without collecting performance statistics in order to reduce the effects of the assumptions made in estimating the initial values. It has been possible to increase this warmup time from one year to two years because we now have seven years of demand data. The initial forecast is now based on the first two years of demand rather than the final two years because it was noticed that there was a general down trend in demand during the later years of the data. The effect of having perfect information in the first two years is masked by the two year warmup.

Since the purpose of this project is to compare different forecast algorithms, the algorithms should all have the same starting conditions, i.e., the conditions when statistics are first accumulated, just after warmup. In order to accomplish this, warmup is now exactly the same for all the algorithms. This is done by using the moving average forecast algorithm during warmup, no matter which algorithm is to be used afterward.

OUTPUT (SECTION 3.3) ASSET MONITOR PERFORMANCE CALCULATIONS

REQUISITIONS SHORT

Time-weighted requisitions short, from which the days wait measure is calculated, is now computed with a more accurate approximation. The basic formula for time-weighted units short is still the same as given in Section 2.6 of the Simulator report. Now, however, a better method is used to estimate the number of requisitions represented by these units. Rather than simply estimating the requisitions short from the units short by dividing by the current order size as was done in the previous version, now the number of requisitions short is carried forward as a total and updated by reducing or increasing its value by the same fraction as the change in units short.

For example suppose that at one point in simulated time there is estimated to be 2 requisitions for a total of 10 units of stock on backorder. Assume that two more requisitions are placed for a total of six units and that five units are received from the supplier. After this there will be 10 + 6 - 5 = 11 units backordered; but how many requisitions? The old way would have estimated the number of requisitions by dividing the number of units by the order size in the current period, i.e. 6/2 = 3 units, then requisitions short = 11/3 = 3.67. The new method estimates the <u>additional</u> requisitions on backorder as the same percentage increase as the units (11-10)/10 = 10%; then requisitions short = 2 + 10% = 2.2 in the example.

The new values have tended to be about one-third less than the old one and are considered much more reasonable.

OBSOLESCENCE PENALTY

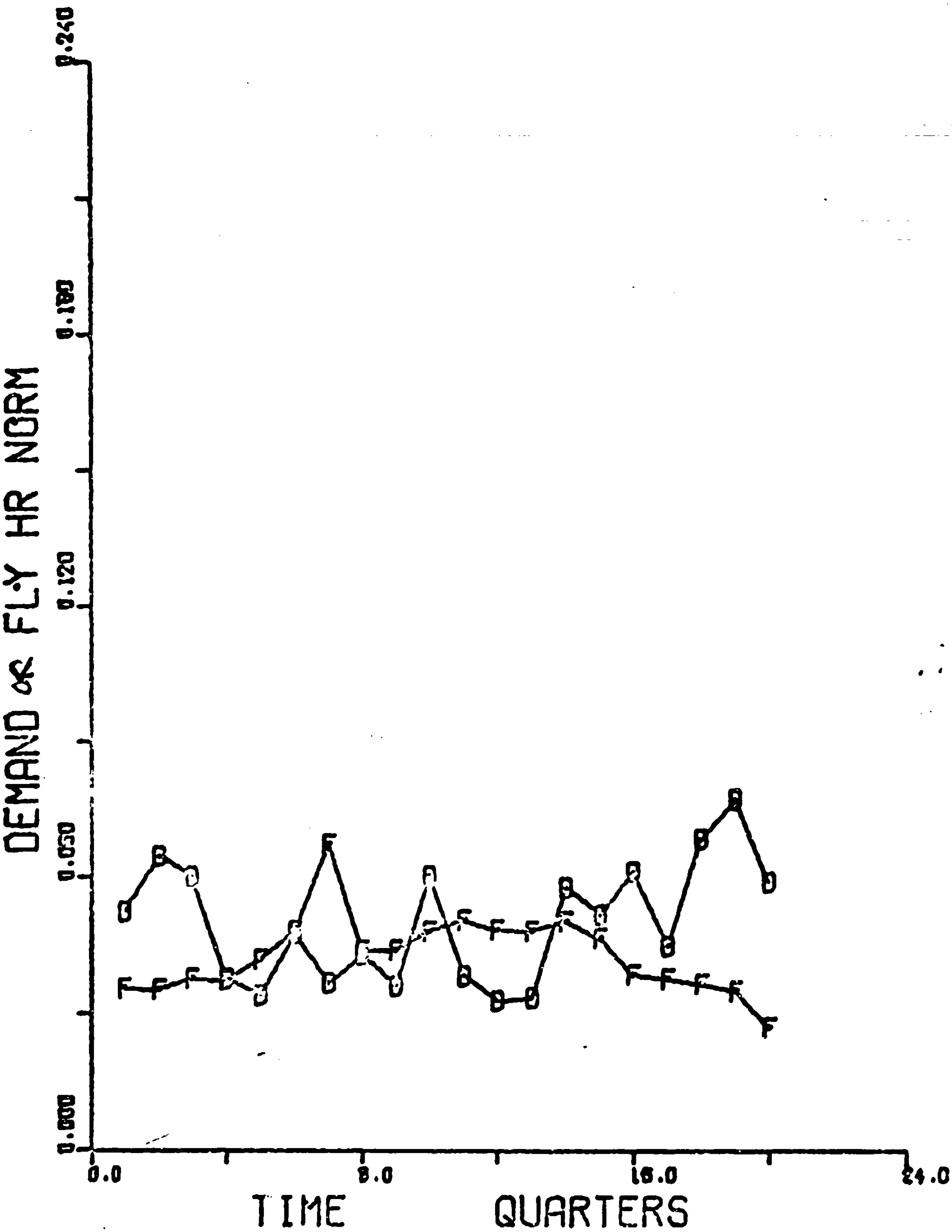
Instead of including an obsolescence rate in with the holding cost rate, now an obsolescence penalty is computed directly and added to the holding cost. This penalty is computed as follows. At the end of the simulation of each item, any on-hand or on-order stock (assets) in excess of the sum of the reorder point and reorder quantity is reduced by the

present value of total future demand and multiplied by the item's unit price. To project future demand, the program data for the period following the simulation is set to the average of the values for the last two years. The rationale for this method of estimating obsolescence is explained in the Deemer and Kruse May 1974 report on pages 15-17.

APPENDIX 2

AGGREGATE NORMALIZED DEMAND QUANTITY AND

FLYING HOURS BY AIRCRAFT SYSTEM


DEMAND & FLY HR NORM
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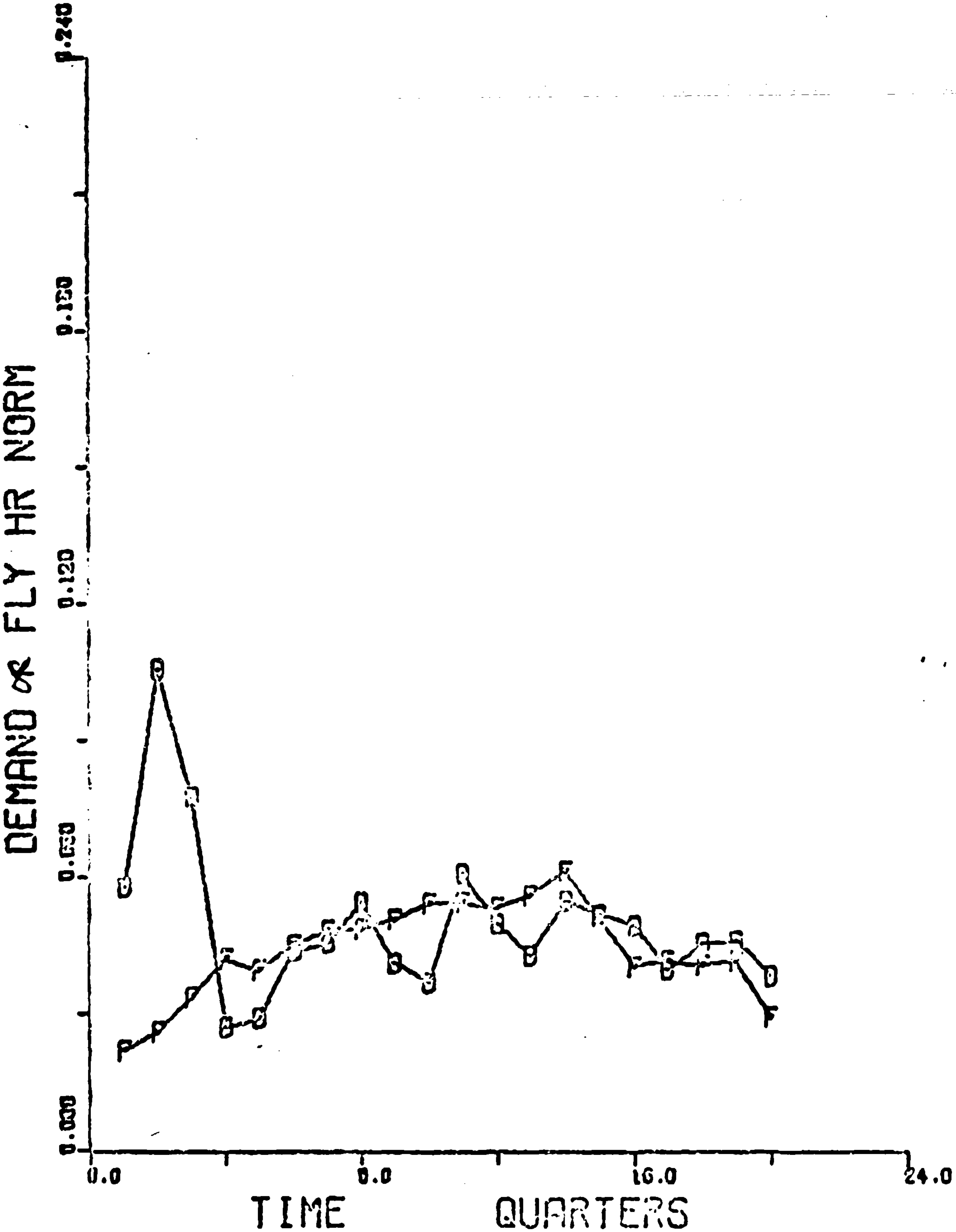
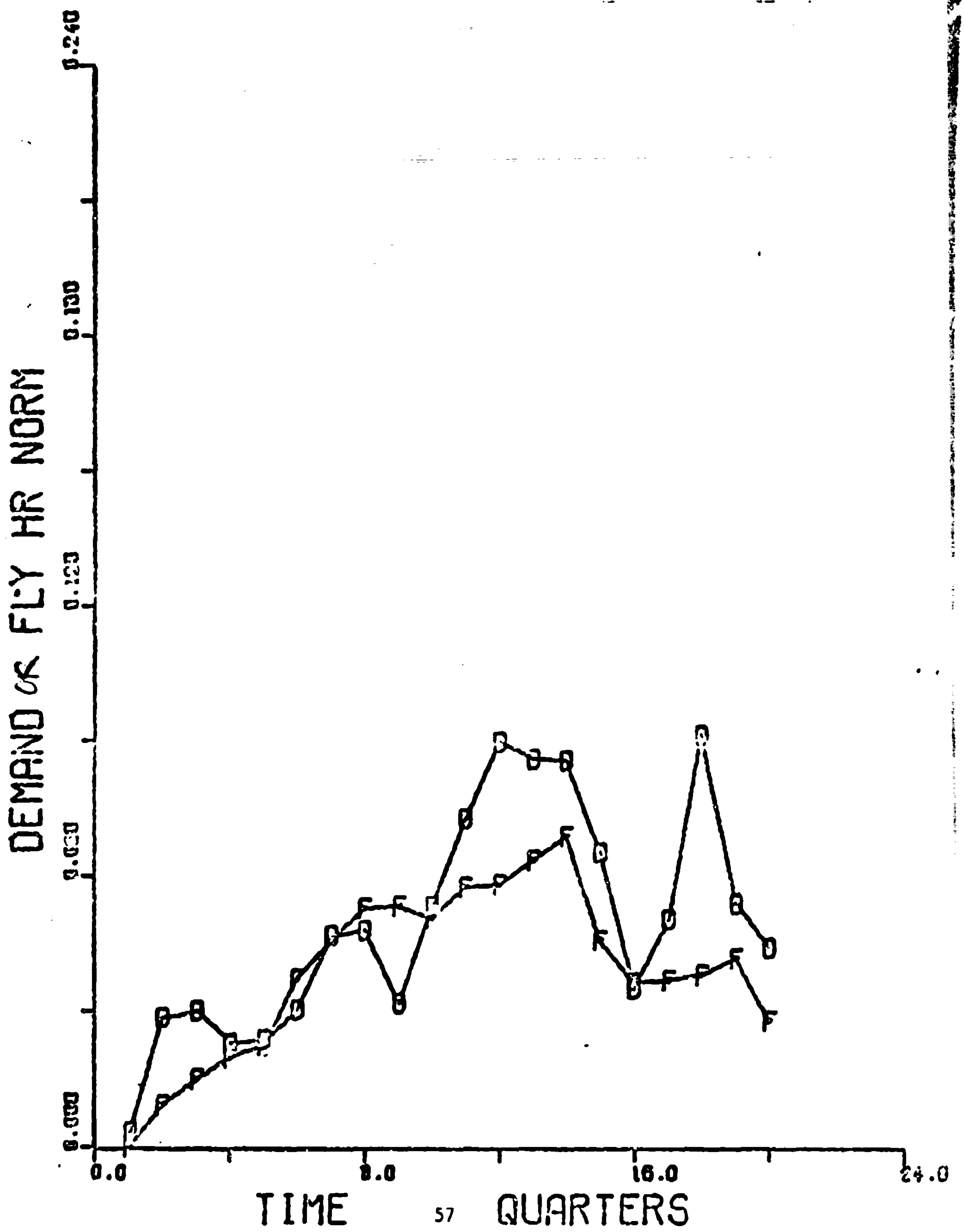
0.060
0.120
0.180
0.240
0.0
8.0
16.0
24.0
TIME QUARTERS

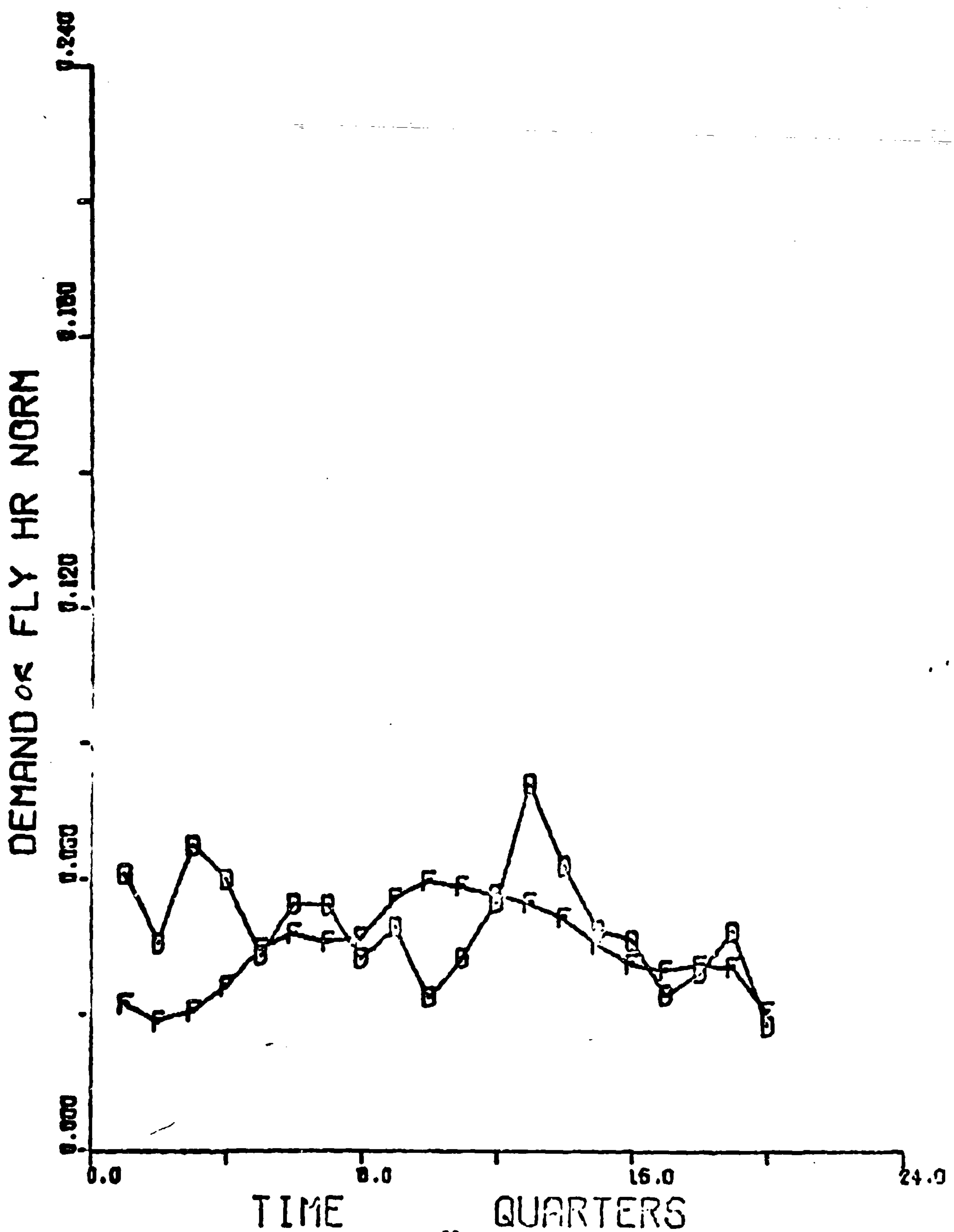
97 PARTS UH-1



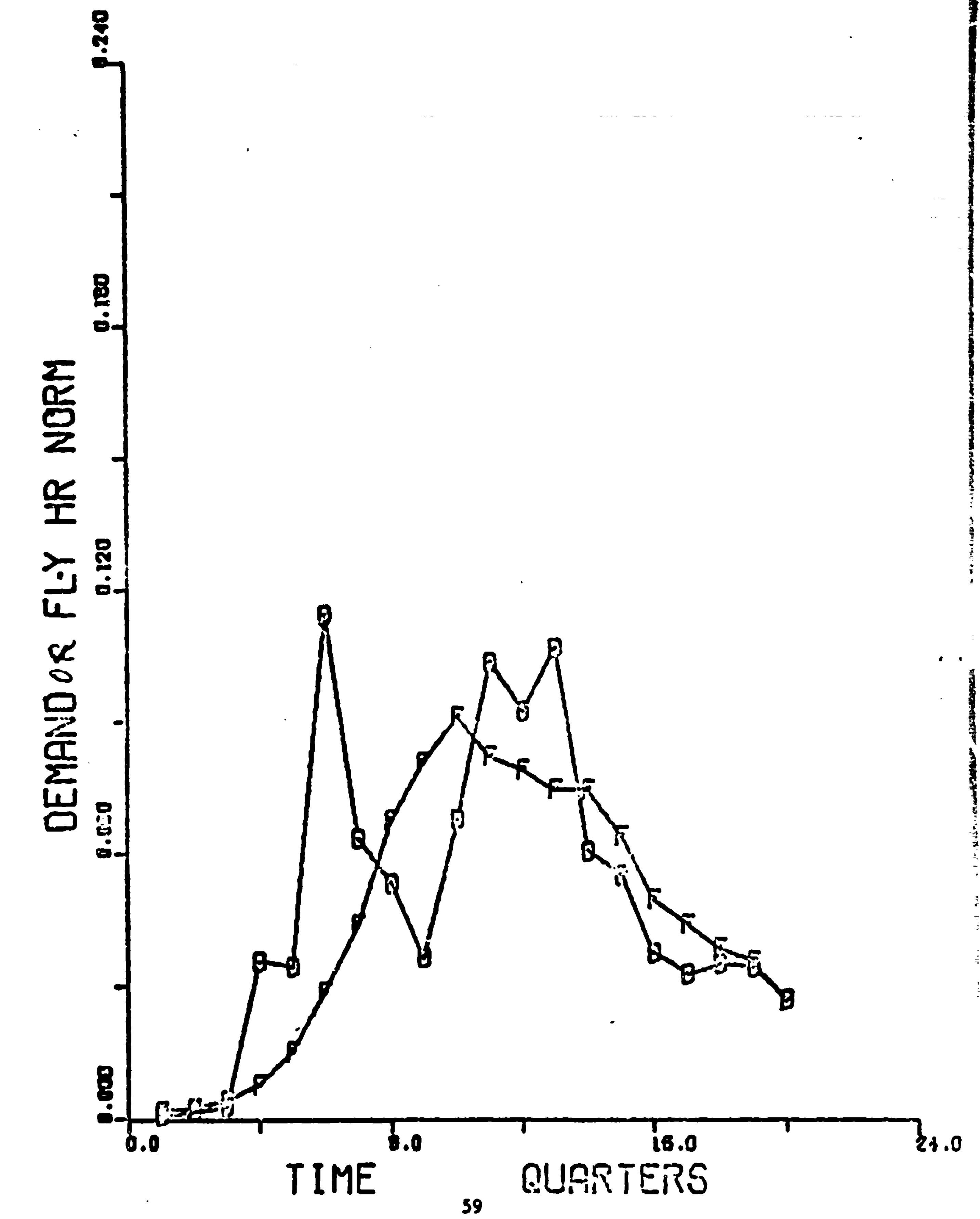
592 PARTS CH-47



101 PARTS CH-54



152 PARTS OV-1



DEMAND OR FLY HR NORM
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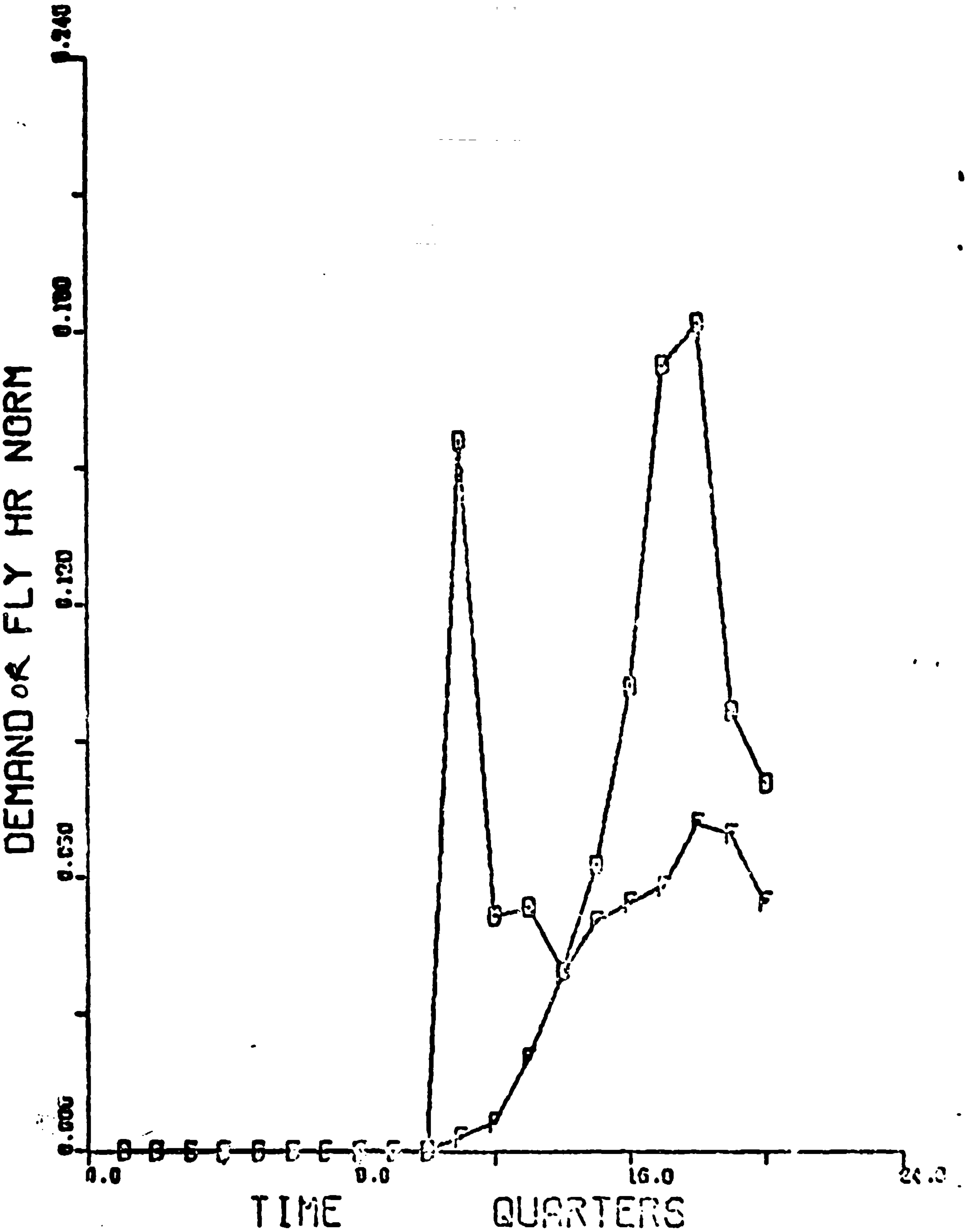
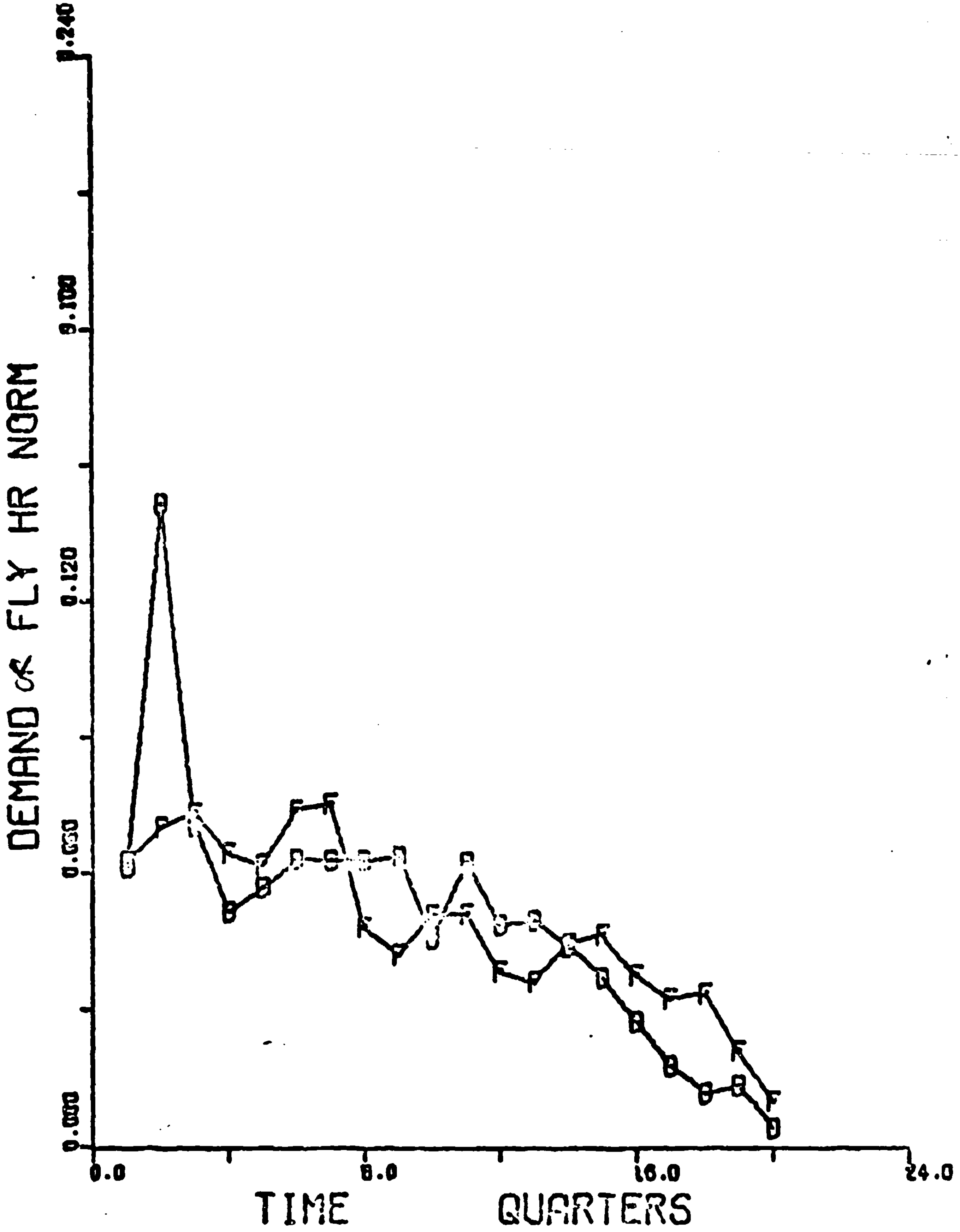
0.180
0.120
0.060
0.000
0.0
8.0
16.0
24.0
TIME QUARTERS

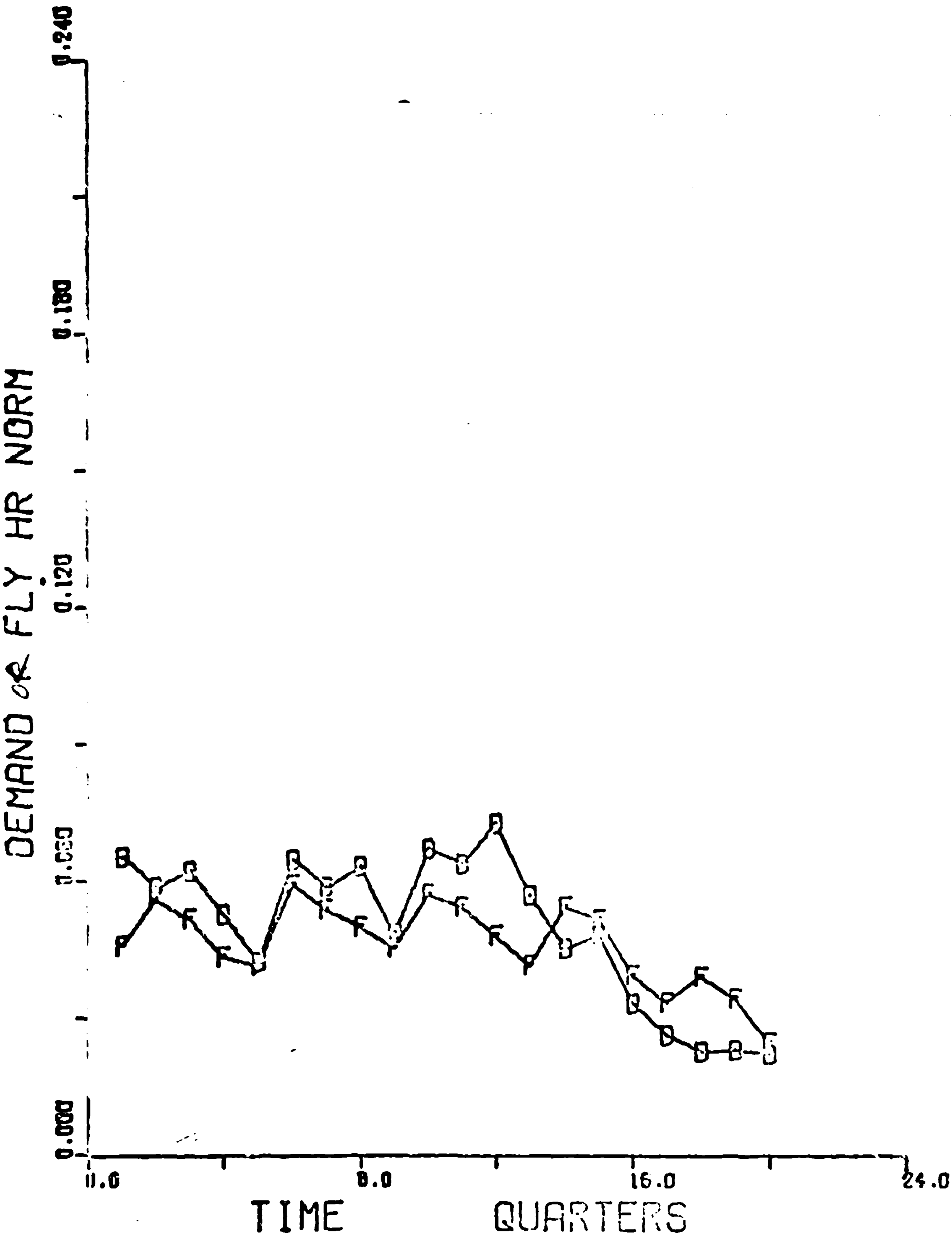
4R PARTS OH-6



171 PARTS OH-58A



105 PARTS OH-23


DEMAND or FLY HR NORM
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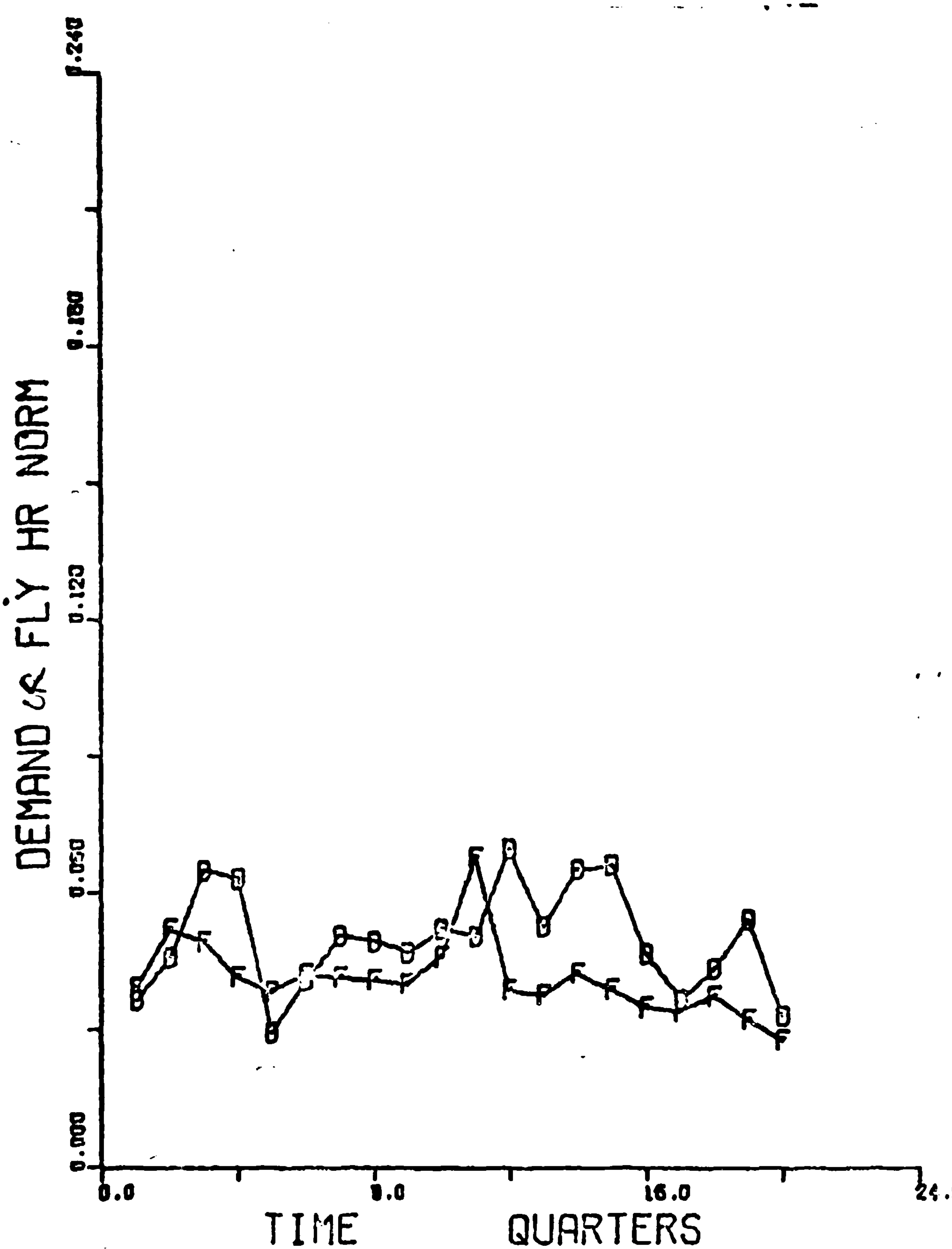
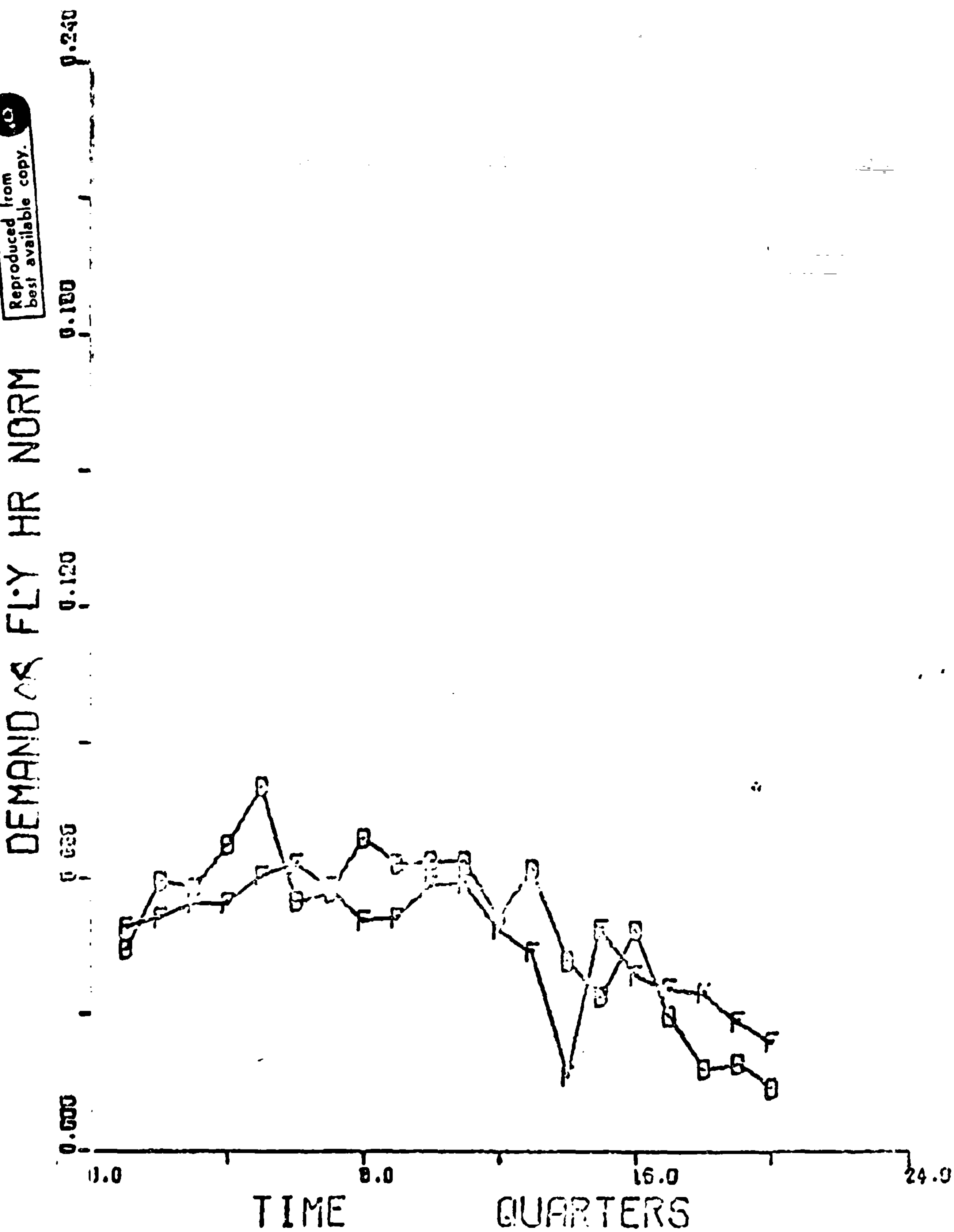
0.120
0.060
0.000
0.0
8.0
16.0
24.0
TIME QUARTERS

U6

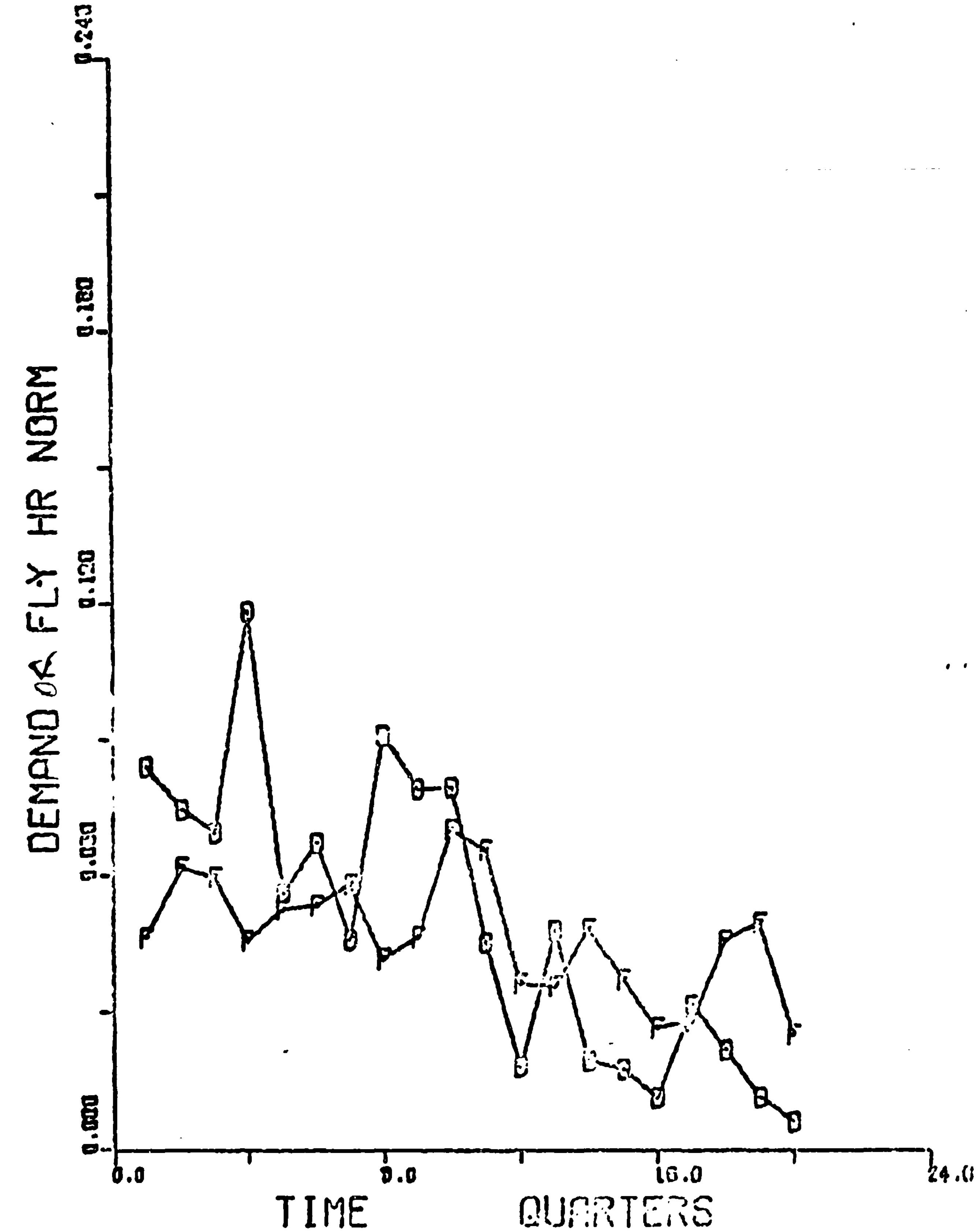


0.240
0.180
0.120
0.050
0.000
DEMAND or FLY HR NORM
0.0
8.0
16.0
24.0
TIME QUARTERS

109 PARTS U-8



181 PARTS CH-13



56 PARTS CH-34

SELECTED BIBLIOGRAPHY

"A Comparative Study of Prediction Techniques," Max Astrachan, Bernice B. Brown and James W. Houghten, Dec 1961, RAND Corp, RM-2811-PR.

Compares seven demand forecasting techniques on B-52 bomber (272 Parts) and Falcon missile (27 components) data.

Techniques: Issue interval (our SEV94); three different upper-bound multiples of issue interval; two service life (normal and log normal); actuarial method.

Issue interval did well on some items. Results were mainly qualitative.

"Fleet Management System Study Age/Maintenance Indicators and Age/Utilization Indicator Relationships, CH-47 Systems," Valentin C. Berger (AVSCOM), Feb 1973, US Army Aviation Systems Command AMSAV-BA-73-1.

Empirical study of relationships between age of 720 CH47A, B and C helicopters and parts utilization. No correlation between age in months or airframe hours and average monthly utilization or down-time per flying hour. Found only slight correlation between utilization and downtime. Attributed to newness of the aircraft system and to Army preventive maintenance.

"Characteristics of Demand for Aircraft Spare Parts," Bernice B. Brown, July 1956, RAND Corp. R-292.

Data: 193 B-47 airframe parts on at least ten different aircraft types.

Period: Up to 13 months covered.

No perceptible linear relationship between demand and flying hours.

"A Bayesian Approach to Demand Estimation and Inventory Provisioning," G.F. Brown and W.F. Rogers, July 1972, Center for Naval Analyses RC-214 DDC-AD-748608.

Theoretical not empirical. Assumes that demand versus flying hours is poisson distributed with uncertain mean. Shows that posterior distribution results in low correlation between demand and flying hours.

"The Relationship of Resource Demands to Airbase Operations," Harrison S. Campbell (RAND), Jan 1963, RAND Corp. RM-3428-PR, DDC-AD 295564 DLSIE-LD 05415.

Compares several alternative program elements. Only flying hours explains a significant fraction of demand variation.

"A Study of Usage and Program Relationships for Aviation Repair Parts," Marvin Denicoff and Sheldon E. Haber, George Washington University, Aug 1962.

Found poor correlation between usage (demand) and flying hours.

"DSA Stock Fund Sales Relationships to DoD Troop Strength," DSA Hq. Report (DSAH-LXE), April 1968, DDC-AD 832572.

Found high correlation between troop strength and stock fund sales in dollars.

"Learning Curve Approach to Reliability Monitoring," J.T. Duane (General Electric Co., Erie, Pa.), April 1964, IEEE Transactions on Aerospace 2,2 page 563.

Learning curves for reliability improvement of 5 aircraft items (2 hydro-mechanical, 2 generators and one complete jet engine) were studied. Failure rate was found to be inversely proportional to the square root of total cumulative flying hours.

"Characteristics of Demand Distributions for Aircraft Spare Parts," W.M. Fawcett, et al, Nov 1966, General Dynamics Corp.

Data: One B-58 wing, 53 types of part, unit price from $10 to $10000. Total flying hours = 39000.

Period: Jan 1963-Dec 1965.

Demand considered to be distributed over flying hour intervals rather than time. Chi-square comparison of demand experience with Simple and Geometric Poisson distributions. Performance not reported.

"Rotatable Pool Allowance Forecasting," Report 88, Project 971266 US Navy FMSO, Oct 5, 1972, R.J. Gabriel and K.E. Shank, DDC AD 749693 DLSIE LD 28670.

Hypothesis: direct linear relationship between number of aircraft supported and number of repairs on installed components. Verified (correlation coef $\geq$ .7) for only 33% of cases. A "case" is one type/model/series of aircraft supported at one Intermediate Maintenance Activity. (20 cases) (6 master jet activities supporting 14 type/model/series aircraft of types F-4, A-4, A-6, A-7, F-8. [915 observations total])

Only items with 3 or more repairs per quarter (for given activity) were included.

Time frame: cal yr 1971 (4 quarters)

"Analysis of Program Factor - Demand Relationships for M16 Rifle Parts"(U) Steven Gajdalo, Nov 1969, Confidential, AMCIRO

Informal analysis of ammuntion consumption versus parts demand. Concludes a fractional effect algorithm (equivalent to PARTEF) is best.

"An Evaluation of Program Activity as a Demand Prediction Tool," Oscar A. Goldfarb (Navy Dept) and William A. Smiley (CPT USAF), Aug 1967, Air Force Institute of Technology thesis SLSR-53-67, DDC AD 825142, DLSIE LD17040.

Data: 91 AF items, 213 Navy items, reparable only.

Period: Jul 65-Mar 67.

Aircraft: F-4

Studied how well flying hours could be forecasted and how well demand correlated to actual hours flown.

Results: Program activity (flying hours) can be forecasted accurately (usually overforecast); Program activity and demand were significantly correlated for 63% of the Navy items and 97% of AF. (Density and sorties did not correlate as well); Results for very low demand items (lots of zeroes) were not very different from those for higher demand.

Author conclusion: "...Program activity changes have little value as a demand prediction tool for over 75 percent of the reparable items examined."

"A Priori Demand Prediction - A Case Study of B-52 Airframe Parts," Thomas A. Goldman (RAND), Jan 1958, RAND Corp RM-2088, DDC AD 144299.

Data: 114 "Hi-Value" airframe parts for B-52.

Period: Feb 1955-Apr 1956.

Divides B-52 parts into three demand levels, high, medium and low, according to "physical and operational characteristics... the demand significance of which had been evaluated with the help of B-47 consumption experience." Statistically signficant chi-square test against actual part consumption for the first 5 quarters of B-52 experience. All demand very low; most parts not demanded at all.

"A Comparison of Usage Data Among Types of Aircraft," Sheldon E. Haber, (George Washington University), Sept 1967, Naval Research Logistics Quarterly 14,3 page 399.

Base level demand only. Navy data. Flying hours may be useful in predicting aggregate requirements over large number of repair parts, but futile for individual line items.

"A Comparative Study of Demand Forecasting Techniques for Military Helicopter Spare Parts," Robert E. Markland (University of Missouri, St. Louis, Mo.), Mar 1970, Naval Research Logistics Quarterly 17,1 pages 103-119.

Also available as a report dated Sept 1969. Work described in more detail in his thesis accepted for Doctorate of Business Administration by Washington Univ. St. Louis, available from University Microfilm Service as 69-15-[illegible].

Data: 60 months, 10 parts applying to UH-1D, OH-23D, CH-47A

Compared various forecasting algorithms using only previous demand and the issue interval as used by Army. Used correlation of forecast to demand as criterion. Best algorithm was triple exponential smoothing but its disadvantages were masked by the experimental methodology.